Projection of adult obesity trends based on individual BMI trajectories

Extended Abstract

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SHORT ABSTRACT

Adult obesity has been increasing in the United States since the 1980s. Combining both observed weight histories of young cohorts and knowledge on age-related weight gain acquired on older cohorts can yield realistic projections of the future burden of obesity. We pooled 69,531 body-mass index (BMI) measures from 20,225 adults interviewed during the National Health and Nutrition Examination Survey. We applied a functional data analysis technique to reconstruct individual BMI trajectories in order to investigate the future evolution of obesity and severe obesity prevalence at 50 as well as the average time spent obese and severely obese between 25 and 50. Preliminary results revealed that obesity prevalence at age 50 can be expected to plateau at around 50% for cohorts today aged 25. This reassuring result masks contrasting evolutions in ethnic subgroups as well as an increase in the proportion of severe forms of obesity among those obese at 50.

EXTENDED ABSTRACT

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) since the 1980s in the United States, from 14.7% in 1976-1980 to 37.9% in 2013-1014.[1,2] Obesity is a risk factor for many major chronic diseases, notably type 2 diabetes [6] and cardiovascular diseases,[7,8] as well as to some types of cancers.[9] Accordingly, obesity is associated with all-cause mortality.[10,11] Obesity has been one of the most important contributors to slow health improvements in the United States over the past decades,[3] and is expected to continue exert a strong influence on US life expectancy.[4,5] Though 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 obesity's effect on health are cumulative. Accordingly, other characteristics of BMI trajectories have been investigated. Duration of obesity, [12] maximum BMI ever attained [13] and weight change[14] have indeed been found associated with changes in the risk of death.

In this context, forming accurate predictions on future trends in several obesity metrics is crucial to assess the future cost of the obesity epidemic. This goal can only be achieved by using information already available on obesity prevalence in young birth cohorts and reasonable assumptions on its future evolution. The most common approach to obesity projection has been extrapolation of prevalence based on past trends.[15-17] This approach does not recognize the fact that obesity is expected to have a strong cohort component, since at the individual level weight attained at a given age greatly determines 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 increased projection accuracy. Other projection methods have taken into account the cohort effect in obesity, but have discretized information on BMI into classes before projection.[5] This results in a loss of information. For instance, the fact that an individual's current BMI is 25.3kg/m^2 is more informative on his future BMI than his belonging to the "overweight" category.

A recent study by Ward et al. has managed to incorporate 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, these authors built a simulation model of height and weight trajectories while accounting for secular trends. This approach for instance predicted that 57.3% of today's US children will be obese at age 35. The present study develops a method of projection that similarly builds on the fact that an individual's BMI is a function of age and indeed can be treated as such. By contrast, the proposed method directly reconstructs any individual's BMI trajectory based on knowledge of its value at specific ages and detection of patterns common across individuals. For any birth cohort, the method thus preserves both available information (the part of the BMI trajectory that has already been observed) and utilizes information gained on earlier cohorts, that have been observed to older ages.

Data and methods

Data source. The National Health and Nutrition Examination Survey (NHANES) is a series of nationally representative surveys of the US civilian non-institutionalized population conducted by the National Center for Health Statistics (NCHS).[19] The surveys include a physical examination by trained technicians in a mobile examination center, during which height and weight of participants are measured. During a home interview, participants are asked their current weight, weight 1 year before survey (if aged 16 or above), 10 years before survey (if aged 36 or above), and at age 25 (if aged 27 or above). The data has been collected on a continuous basis since 1999 (continuous NHANES) and is released in two-year cycles. We pooled all available cycles of continuous NHANES (1999-2016). The dataset analyzed was that of all participants examined between ages 25 and 50 with no missing data on education or smoking status at age 20 (N = 20,225).

Correction for misreporting of past weights. Height and weight are known to be misreported.[20-22] We therefore computed all BMIs with measured height, and used measured weight for current BMI. We first computed past BMIs using reported weights. We then corrected each individual's past BMIs adding to them the difference between current measured and reported BMIs. 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 BMIs measured at previous NHANES cycles (Figure 1). For this reason, we added as a corrective term the difference between the two surfaces. This correction is therefore age, cohort and sex-specific.

Functional data analysis. The mean (SD) number of observations per individual was 3.4 (0.7). We defined strata based on sex, race/ethnicity (non-Hispanic black, non-Hispanic white, Hispanic, other race), educational attainments (high school or less, some college degree, college graduates), and smoking status at age 25 (smoker/non-smoker). In each stratum, we applied a recently developed Bayesian hierarchical model for the smoothing of functional data. [23] Briefly, the method assumes that BMI trajectories within each stratum are independent realizations of the same Gaussian process subject to a common level of measurement error. A Gaussian process prior is set for the mean function, and an Inverse-Wishart process prior for the covariance function. The reconstruction of an individual’s BMI trajectory therefore uses information specific to that trajectory but is also informed by the trajectories of the other members of the same stratum, some of whom have been observed to the oldest age considered, namely age 50. Figure 2 plots examples of individual reconstructions.

Obesity metrics considered. We consider four obesity metrics : prevalence of obesity at age 50 (BMI > 30 kg/m^2), prevalence of severe obesity at age 50 (BMI > 40 kg/m^2), time spent obese between 20 and 50 years and time spent severely obese between 20 and 50 years. Sampling weights are utilized to obtain unbiased national projections.

Preliminary Results

Average BMI trajectory between 25 and 50. Both the initial level of BMI (at age 25) and patterns of age-related trends differed between groups. For example, among non-smoking females with lowest educational attainment, the “Other race” group showed markedly lower mean BMI across the age span investigated. Though starting with similar values of mean BMI at 25, weight gain with age was found accelerated among non-Hispanic Black vs. non-Hispanic White and Hispanic women (Figure 2a).

Obesity prevalence at age 50. Obesity prevalence at 50 will continue to increase and is predicted to cross 50% in both males and females (Figure 3, top panels). In females, while it is 46.1% (95% Uncertainty Interval [UI], 43.7 % - 48.6%) for the cohort currently aged 50, it is expected to peak at 54.8% (95% UI, 51.5% - 58.0%) for those born 1979-82. The predicted plateauing of female obesity prevalence at 50 for young cohorts (born after 1980) echoes the plateauing of obesity prevalence already observed at younger ages in these cohorts. In males, obesity prevalence at 50 is currently 40.7% (95% UI, 38.2% - 43.3%), and is expected to attain 50.8% (95% UI, 46.3% - 55.4%) for the 1983-86 birth cohort. Projection by ethnic groups revealed strong differences. For instance, obesity prevalence at 50 in non-Hispanic Black women is expected to reach 79.3% for those born 1983-1986 (95% UI, 72.7% - 85.6%; Figure 4).

Severe obesity prevalence at age 50. The model predicts severe obesity at 50 will increase rapidly in females, from 9.9% (95% UI, 8.6% - 11.3%) to 15.7% (95% UI, 13.7% - 17.9%) for those born 1979-82, then remain stable (Figure 3, lower panels). Similarly, male severe obesity at 50 will increase in the next two decades, from its current value of 4.8% (95% UI, 3.9 – 5.7) to 8.1% (95% UI, 6.1% – 10.4%) for the 1983-86 birth cohort.

First conclusions

Obesity is a state that is stable from one age to the next. This can be leveraged for projections, since most of the information on future obesity can as a consequence be found in current status of individual members of the cohorts. The fact that obesity is a complex risk factor, whose effects can be felt decades after it has been acquired and be subject to reverse causation (diseases caused by obesity leading to weight loss) also calls for systematic reconstruction of BMI trajectories. For these two purposes, this study makes use of a flexible functional data analysis technique.

Preliminary results show that prevalence of obesity at age 50 is expected to plateau at ~ 50%. This population-level value masks large variations across ethnic groups as well as a more pronounced increase in severe obesity prevalence.

Figures

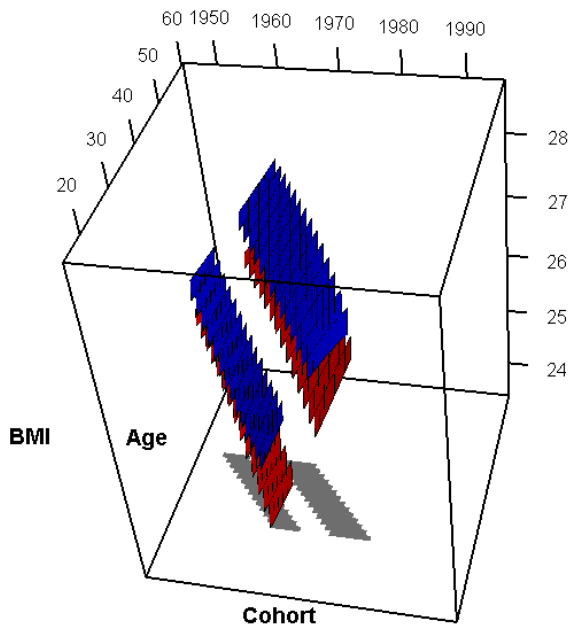

Figure 1. Mean female BMI surface, estimated using either measured BMI (blue) or reported BMI 10 years before survey after first correction (red). In each case, the BMI surface was estimated with a Generalized Additive Model with a Gamma distribution, using survey weights for unbiasedness. Measured BMIs were collected either during NHANES III or continuous NHANES cycles.

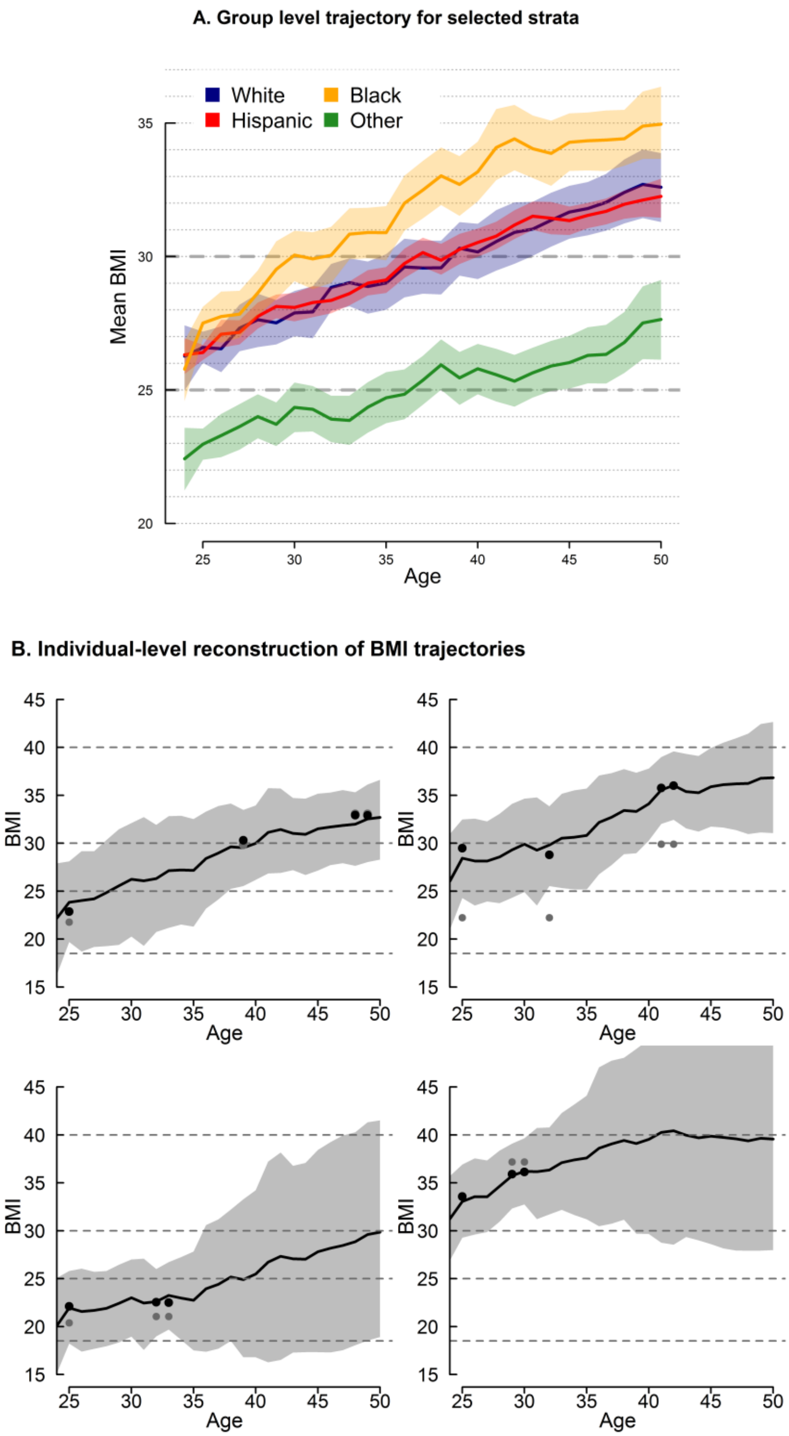

Figure 2. Reconstruction of BMI trajectories

Panel A shows the average posterior (with 95% Uncertainty Interval [UI]) of the mean BMI function for non-smoking females with lowest educational attainment (high school or less).

Panel B shows examples of BMI trajectories (average posterior and 95% UI) of individuals that all belong to the same stratum (black non-smoking females with lowest educational attainment). BMIs based on uncorrected reported weights are shown in grey. BMIs corrected for misreporting, used in the analysis, are shown in black. The reconstruction of the trajectory of young individuals (bottom plots) is informed by both available information on their current and past BMIs, as well as on the trajectories of older individuals (top plots).

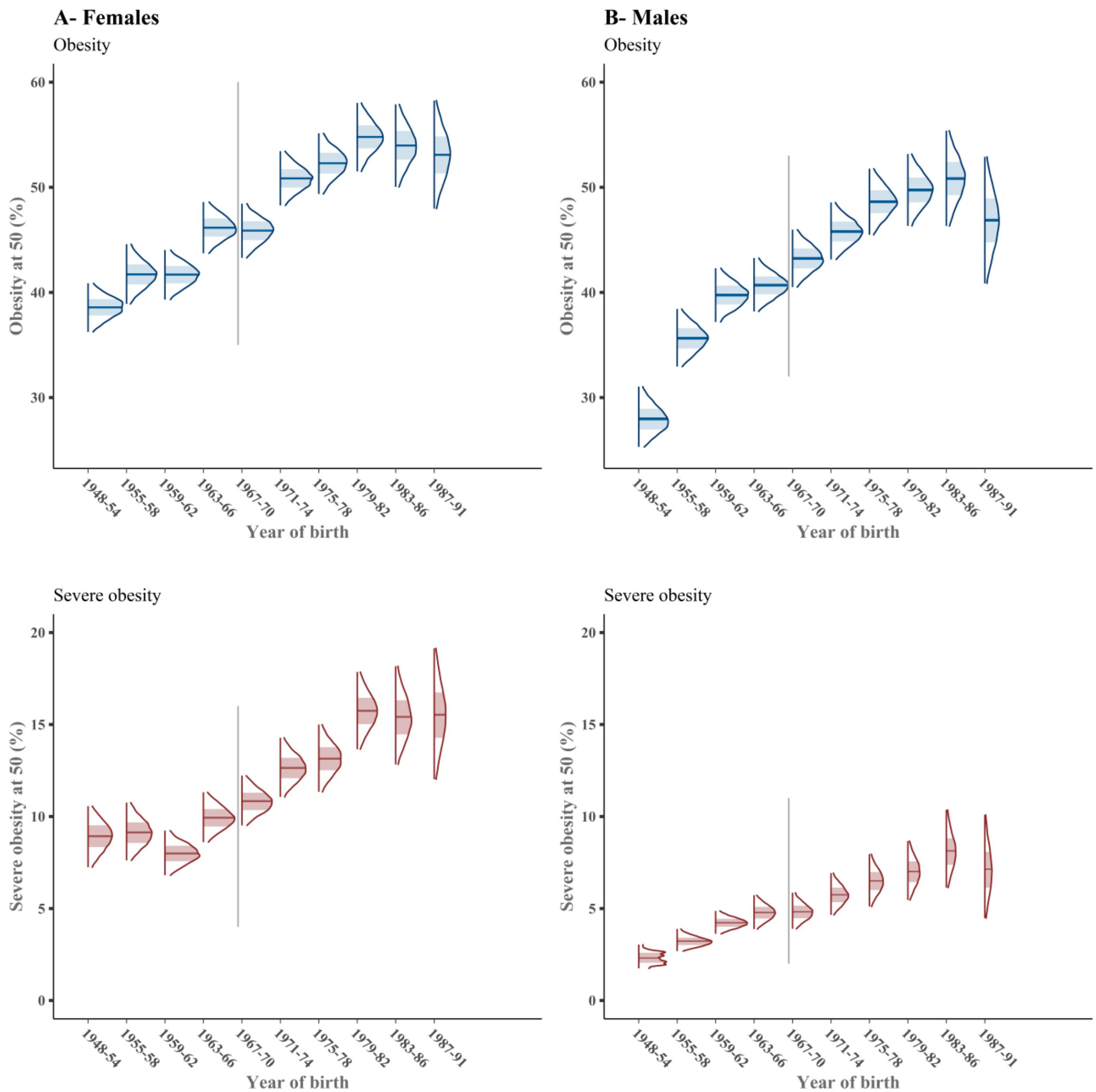

Figure 3- Projection of obesity and severe obesity at age 50, by sex.

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

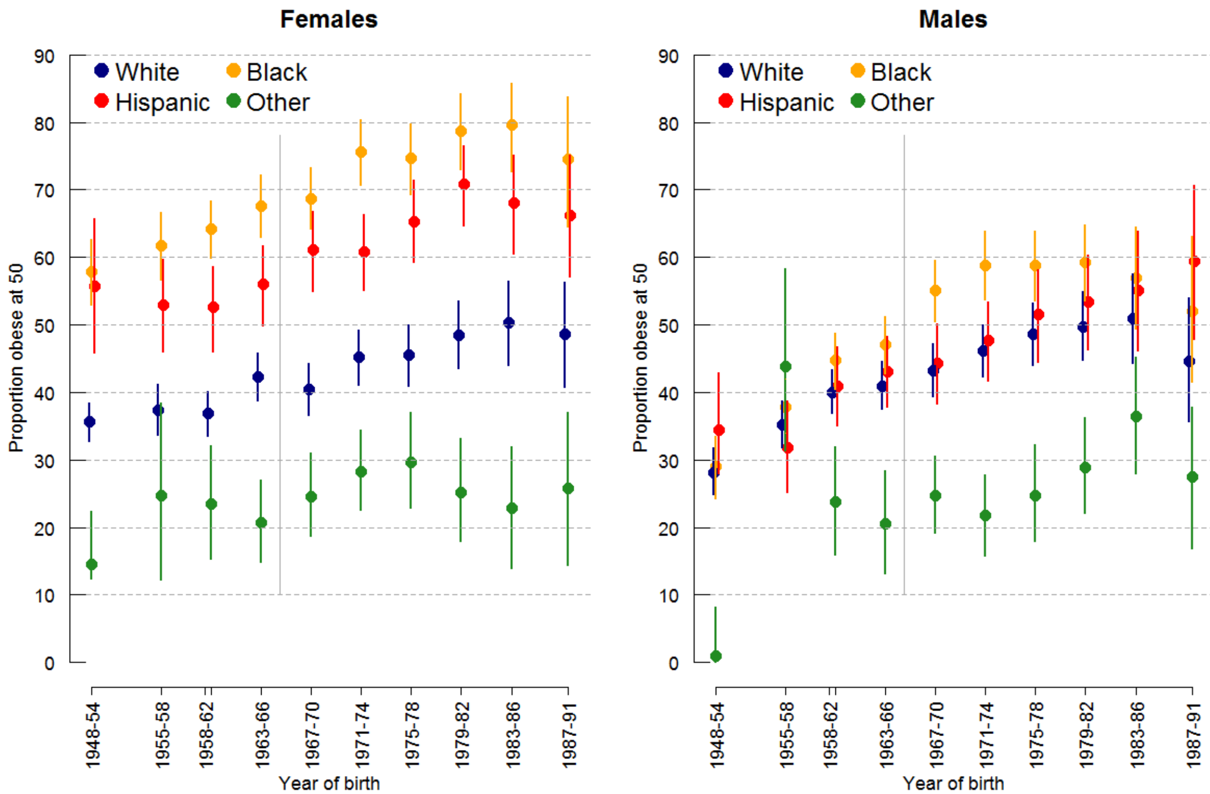

Figure 4. Projection of obesity at age 50, by sex and race/ethnicity.

Posterior means and 95% UIs.

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