Trends in group inequalities and interindividual inequalities in BMI in the United States, 1993–2012[1–5]

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ABSTRACT

Background: Marked increases in mean body mass index (BMI) and prevalence of obesity and overweight in the United States are well known. However, whether these average increases were accompanied by changing dispersion (or SD) remains understudied.

Objective: We investigated population-level changes in the BMI distribution over time to understand how changes in dispersion reflect between-group compared with within-group inequalities in weight gain in the United States.

Design: Using data from the Behavioral Risk Factor Surveillance System survey (1993–2012), we analyzed associations between mean, SD, and median BMI and BMI at the 5th and 95th percentiles for 3,050,992 non-Hispanic white, non-Hispanic black, and Hispanic men and women aged 25–64 y.

Results: Overall, an increase of 1.0 in mean BMI (in kg/m^2) was associated with an increase of 0.70 (95% CI: 0.67, 0.73) in the SD of BMI. A change of 1.0 in median BMI was associated with a change of 0.18 (95% CI: 0.14, 0.21) in the BMI value at the 5th percentile compared with a change of 2.94 (95% CI: 2.81, 3.07) at the 95th percentile. Quantile-quantile plots showed unequal changes in the BMI distribution, with pronounced changes at higher percentiles. Similar patterns were observed in subgroups stratified by sex, race-ethnicity, and education with non-Hispanic black women and women with less than a high school education having highest mean BMI, SD of BMI, and BMI values at the 5th and 95th percentiles.

Conclusions: Mean BMI and the percentage of overweight and obese individuals do not fully describe population changes in BMI. Increases in within-group inequality in BMI represent an underrecognized characteristic of population-level weight gain. Crucially, similar increases in dispersion within groups suggest that growing inequalities in BMI at the population level are not driven by these socioeconomic and demographic factors. Future research should focus on understanding factors driving inequalities in weight gain between individuals. *Am J Clin Nutr* 2015;101:598–605.

Keywords body mass index, distributional change, health inequalities, obesity, BRFSS, Behavioral Risk Factor Surveillance System, socioeconomic status

INTRODUCTION

Many descriptions of population change in BMI relied on the change in mean BMI or point estimates such as the prevalence of obesity to summarize changes in the overall distribution (1–3). In high-income countries such as the United States, obesity and overweight prevalence rose sharply over the past 2 decades (1, 4, 5). Previous research has shown greater rates of increase in mean BMI in lower socioeconomic groups (6) and women compared with men (7) with an inference of widening inequalities between social groups. However, few studies examined whether inequalities in weight gain are occurring within social groups in the United States or specific segments of the population, which is a measure of interindividual inequalities rather than between group inequalities. A study of adults in Mississippi showed the greatest change over time in the upper tails of the BMI distribution (8). Another study showed greater increases in upper deciles of the BMI distribution accompanied by increases in the variance across United States for birth cohorts from 1882 to 1986 (9). Similar patterns were observed in Union Army veterans (10) and Swiss conscripts (11). Recent work that used National Health and Nutrition Examination Survey (NHANES)[6] data showed disproportionate increases in the 90th percentile of BMI distribution in a graphical analysis, although numeric estimates were not reported (12). Lastly, there has also been evidence of greater increases in BMI at higher quantiles within socioeconomic and demographic groups (13).

Our study built on this formative work on individual inequalities in weight gain to look at individual inequalities in

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[3] Supplemental Figures 1–3 and Supplemental Tables 1–7 are available from the "Supplemental data" link in the online posting of the article and from the same link in the online table of contents at http://ajcn.nutrition.org.

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[6] Abbreviations used: BRFSS, Behavioral Risk Factor Surveillance System; NHANES, National Health and Nutrition Examination Survey; QQ, quantile-quantile; SES, socioeconomic status.

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weight gain in the United States by using dispersion or the SD as a measure of inequality. To our knowledge, this work is the first to consider the SD in BMI to reflect inequalities in weight gain in the United States. The theoretical basis to examine population-level dispersion was outlined by Murray et al. (14), who described how broader distributional changes captured by changes in dispersion reflected inequalities in health. Murray et al. (14) offered the following 2 complementary approaches to studying health inequalities: *1*) the conventional approach of measuring social group inequalities by differences in mean values or the prevalence of health outcomes between groups and *2*) individual inequality as manifested by differences between individuals within social groups or between segments of the population to describe inequalities in the distribution of health outcomes (14).

In this article, we examined the BMI distribution in the United States in the past 2 decades and explore the relevance of ideas of population change and inequality developed by Murray et al. (14) by adopting the group inequality compared with individual inequality framework to understand patterns of change. We used the Behavioral Risk Factor Surveillance System (BRFSS) surveys of non-Hispanic whites and non-Hispanic blacks aged 25–64 y from 1993 to 2012 and Hispanics aged 25–64 y from 2001 to 2012. Our analysis addresses the following questions: *1*) For the entire US population, how are changes in mean BMI related to inequalities in rates of change of particular segments (percentiles) of the BMI distribution? *2*) For particular groups (race/ethnic, sex, and education categories) given changes in mean BMI, how do changes in distributional characteristics within these groups reflect interindividual inequalities. Investigating distributional changes in BMI within socioeconomic and demographic groups, our study considered possible explanations for and implications of changes in interindividual inequalities.

METHODS

Data sources

Data were from the BRFSS, which is a nationally representative, cross-sectional survey conducted by the Behavioral Risk Factor Surveillance Branch of the CDC since 1984 (15). In the early 1980s, states lacked surveillance data on health risks and behaviors needed to inform evidence-based health policies and programs. The BRFSS was designed as a coordinated mechanism to collect state-level surveillance data, expanding from 15 states in 1984 to all 50 US states and the District of Colombia, Puerto Rico, Guam, and the US Virgin Islands. Data from the BRFSS have been shown to be comparable with other nationally representative data sets such as the NHANES or National Health Interview System (16).

Study population and sample size

The population included in this study consisted of individuals pooled from BRFSS surveys from 1993 to 2012. Our sample included 3,050,992 individuals aged 25–64 y who were living in 48 states and Washington, DC (excluding Alaska, Hawaii, and nonstate territories). This sample included data collected every year from 1993 to 2012 for all states except Wyoming, in which data were only collected from 1994 onward. From 1993 to 2000, we used BRFSS data only on non-Hispanic whites and blacks because BRFSS surveys before 2001 included only 3 mutually exclusive racial-ethnic categories of non-Hispanic white, non-Hispanic black, and other, with Hispanics grouped within the other category. From 2001 onward, Hispanic was included as a separate racial-ethnic category, allowing us to present analyses for Hispanics from 2001 to 2012. We excluded pregnant women, individuals with missing data on key variables of interest (e.g., BMI, age, sex, race, state of residence, and highest year of education), and individuals with extreme values of BMI (in kg/m^2; $<$12.0 or $>$70.0). We also restricted the sample to only 25- to 64-y-old adults to ensure that our analysis is consistent with previous work and also because use of BMI may not be appropriate among older individuals because of evidence of increasing body fat at similar levels of BMI among older adults compared with younger ones (17) and artificial increase of BMI due to shrinkage in stature in older adults (18). Although there is no well-defined age threshold for the appropriateness of BMI, other authors argued that measures such as central adiposity may better reflect health risks associated with obesity for older adults (19). Unfortunately, these measures were not available in the BRFSS. Data availability also restricted our sample to include only non-Hispanic whites, non-Hispanic blacks, and Hispanics, with the exclusion of non-Hispanic Asians and other racial-ethnic categories.

Outcome

The outcome of interest was BMI measured as a ratio of weight (kg) to the square of height (m). Fifth and 95th percentiles and the SD of the BMI distribution were used as outcomes to study changes in the shape of the distribution over time relative to 2 central tendencies of mean and median BMI.

Key independent variables

Key explanatory variables included age, which was divided into 5-y groups and treated as a categorical variable, sex, race-ethnicity (non-Hispanic white, non-Hispanic black, and Hispanic), and educational level (less than a high school education, high school graduate, some college education, and college graduate). In our consideration of relevant socioeconomic variables, we excluded income because of evidence of a reciprocal relation between BMI and income (20, 21).

Analysis

BRFSS data from 1993 to 2012 were pooled to allow for the comparison of distributional changes over time. We conducted analyses by sex, race, and educational level to disaggregate distributional changes within subgroups. Disaggregating by only sex, we had 2 subgroups (women and men) pooled across race-ethnicities and educational levels; stratifying by race-ethnicity, we had 3 subgroups (non-Hispanic white, non-Hispanic black, and Hispanic) pooled across sex and educational levels. Stratifying by both race-ethnicity and sex, we had 6 subgroups (non-Hispanic white women, non-Hispanic white men, non-Hispanic black men, non-Hispanic black women, Hispanic women, and Hispanic men) pooled across educational levels. Stratifying by educational level, we had 4 subgroups pooled across sex and race-ethnicity; and with stratification by both educational level and sex, we had 8 subgroups across race-ethnicity categories.

Within each group, we adjusted for relevant covariates by using a linear regression approach that involves regressing BMI on covariates and adding residuals from the model to the grand mean of BMI. For analyses on all individuals, we adjusted BMI for age, sex, and race-ethnicity across the entire sample. When stratifying by sex and by sex and educational level, we adjusted by only age and race-ethnicity, and when stratifying by both sex and race-ethnicity, we adjusted only by age. Using adjusted BMI, we computed distributional parameters (mean, SD, and 5th and 95th percentiles) for all individuals as well as all subgroups for each survey year. Computations were weighted by using sample weights to obtain distributional variables representative of the US population in each survey year. Sample weights were renormalized for subgroup analyses. Stata version 13.1 (StataCorp), R version 3.1.1 (the R Foundation for Statistical Computing), and RStudio 0.98.1028 programs were used for all analyses.

Analysis of specific variables in the BMI distribution

To characterize the distribution, our study examined changes in mean and median BMI (centrality), the SD of BMI (spread or dispersion), and the 5th and 95th percentiles of BMI (position of tails) to more fully illustrate distributional changes in BMI in the United States. Fitted lines for changes in these variables over time were plotted for all individuals as well as subgroups disaggregated by sex, race-ethnicity, and educational level. Models for subgroup analyses contained interaction terms to examine different rates of change in BMI over time for different groups. Differences in changes over time between reference and nonreference categories were tested by using Wald tests. For all models, units of analysis were BRFSS survey years.

Further examining changes in our parameters of interest, we conducted regression analyses. We analyzed the relation between *1*) mean BMI and outcomes of the SD of BMI and *2*) median BMI and the outcomes of 5th and 95th percentiles of BMI. These analyses were conducted for the total population as well as subgroups disaggregated by sex, race-ethnicity, and educational level. Fitted lines for relative changes in these variables were plotted for all individuals as well as subgroups disaggregated by sex, race-ethnicity, and educational level. Analytic models tested interaction terms between race and sex and educational level and sex, which allowed relations between distributional variables to differ in these subgroups. Differences in estimated associations between reference and nonreference categories were tested using Wald tests.

Sensitivity analyses

We conducted 2 sensitivity analyses. First, we examined whether changes in height were driving distributional changes in BMI. For example, the loss of height in specific segments of the population could have resulted in increasing BMI with expanding variance over time. We examined correlations between BMI and height separately for women and men over survey years and adjusted for these small associations by changing the power of height as the denominator of BMI by using the formula

$$\text{Weight} \div \text{height}^{x} \qquad (1)$$

and manipulating the value of x from 0.10 to 3.0 until the smallest correlations between BMI and height were observed (22). We compared changes in the new measure of BMI (BMI*) that was minimally correlated with height and changes in BMI over survey years. For our second sensitivity analysis, we used the coefficient of variation (CV), which is:

$$\text{CV} = \text{SD} \div \text{mean} \qquad (2)$$

to assess changes in dispersion independently of the mean (23).

Graphical analysis of patterns of BMI distributional changes

We used quantile-quantile (QQ) plots to examine patterns of distributional change in BMI (24). A QQ plot was constructed by plotting percentiles of BMI from the most-recent survey against percentiles of BMI from the baseline survey. If there was no change in distributions between the 2 survey years the points would lie on the line of the equality ($y = x$). Points above the line represented increases in BMI at the same percentile in the most recent year from baseline, whereas points below the line represented decreases at the same percentile. If the entire distribution were to experience an increase in BMI, the QQ plot would show a uniform upward shift of points from the line of equality. However, if distributional changes were concentrated in the lower and upper percentiles, the QQ plot would show deviations from the line of equality only in these groups. In general, QQ plots are effective in presenting changes at the tails of distributions.

We constructed QQ plots for all individuals as well as for 16 subgroups stratified by sex, race-ethnicity, and education by plotting BMI percentiles in 1998, 2001, 2003, 2008, and 2012 against surveys from 1993. For Hispanics, we chose 2001 instead of 1993 for the reference year because information specific to Hispanic populations was available only from 2001 onwards.

Ethical review

The BRFSS was approved centrally at the Institutional Review Board at the CDC as well as review boards in each US state. Oral consent was obtained from all participants. The study was evaluated by the Institutional Review Board at the Harvard School of Public Health and considered exempt from full review because the analysis includes publicly available, de-identified data.

RESULTS

Table 1 contains descriptive statistics about the sample pooled from BRFSS surveys in 1993–2012. The sample was 50% women. Seventy-eight percent of individuals were self-identified as non-Hispanic white, 11% of individuals were non-Hispanic black, and another 11% of individuals were Hispanic across all survey years. Less than 10% of the sample had less than a high school education, 28% of the sample were high school graduates, 27% of the sample had some college education, and 35% of the sample were college graduates.

In the following 2 sections we describe *1*) how the BMI distribution changed over time and *2*) how the tails (5th and 95th percentiles) and spread (SD) of the BMI distribution were related to the average (mean and median) change.

TABLE 1
Descriptive statistics for adults aged 25–64 y (n = 3,050,992)[1]

	Percentage
Women	50.0
Men	50.0
Non-Hispanic white	77.6
Non-Hispanic black	11.1
Hispanic	11.3
Non-Hispanic white women	38.5
Non-Hispanic white men	39.1
Non-Hispanic black women	6.0
Non-Hispanic black men	5.1
Hispanic women	5.5
Hispanic men	5.8
Less than a high school education	9.6
High school graduate	28.3
Some college education	27.1
College graduate	35.0

[1]Source: Behavioral Risk Factor Surveillance System surveys from 1993 to 2012 (15). Statistics were weighted by using sample weights normalized for merged survey cycles.

Changes in distributional variables of BMI over time

Changes in specific distributional variables of BMI over time are presented in **Figure 1** with fitted models shown in **Supplemental Table 1** and more-detailed information shown in **Supplemental Table 2**. Over the survey cycles, mean BMI increased among all individuals as well as among 23 subgroups, rising from 26.0 to 28.1 overall (Supplemental Table 2). All groups experienced similar rates of increase in mean BMI over time; however, there were differences in mean BMI over survey years (Figure 1, Supplemental Table 2). Mean BMI values were higher overall for men than for women, highest for non-Hispanic blacks, and highest for individuals with less than a high school education over all survey years (Figure 1, Supplemental Table 2). Non-Hispanic black women also had higher mean BMI values than those of any other group including non-Hispanic black men (Figure 1). Overall, women showed greater differences in mean BMI between race-ethnic groups and by educational level than did men (Figure 1).

Increases in mean BMI were accompanied by growing dispersion (SD) over time, showing widening inequalities in BMI. Among all individuals, the SD of BMI rose by more than 30% from 4.6 units in 1993 to 6.2 units in 2012 (Supplemental Table 2), with an average annual increase of 0.083 units (Supplemental Table 1). All groups experienced similar rates of increase in SD of BMI (Supplemental Table 1); however, there were differences in SDs in groups (Figure 1, Supplemental Table 2), with higher levels among women than men, non-Hispanic blacks than other race-ethnic groups, and individuals with less than a high school education and high school graduates than individuals with more education. Non-Hispanic black women also experienced a much-higher SD than non-Hispanic black men did, whereas other race-ethnic groups did not show such marked differences by sex (Figure 1, Supplemental Table 2).

Analyses of the tails of this distribution showed that more change had occurred at the 95th percentile than at the 5th percentile (Figure 1, Supplemental Tables 1 and 2). From 1993 to 2012, BMI at the 5th percentile increased by 0.20 compared with 5.10 at the 95th percentile for all individuals (Supplemental Table 2). This resulted in an annual change of a 0.016 increase in the 5th percentile of BMI compared with an increase of 0.28 in the 95th percentile of BMI, nearly a 20-fold greater rate (Supplemental Table 1). Similar trends occurred for all subgroups (Figure 1, Supplemental Table 1).

Relative changes in distributional variables of BMI

Figure 2 examines how specific variables of the BMI distribution are interrelated (i.e., the relation of mean BMI to SD and the relation of median BMI to 5th and 95th percentiles). For all groups, as mean BMI increased, the SD increased. **Supplemental Table 3** contains fitted models for the SD of BMI and mean BMI, which show that, as mean BMI increased by 1.0, the SD of BMI increased by 0.70 units overall. There were small differences in associations between mean BMI and the SD of BMI by sex, race-ethnicity, or educational level. However, there was much-greater dispersion among women than men at the same value of mean BMI. For example, on the basis of regression models shown in Supplemental Table 3 fitted to Figure 2, at the mean BMI across survey years (27.4), the predicted SD for women was 6.5 units, 43% greater than the predicted SD of 4.5 for men. Similarly, disaggregating by sex and race-ethnicity, non-Hispanic white women had greater levels of SD than any other group.

Supplemental Table 3 and Figure 2 show changes in 5th and 95th percentiles relative to median BMI, which mirrored previously noted differences in annual changes in the upper tail compared with lower tail. Overall, as the median BMI increased, the BMI value at the 5th percentile increased by 0.18, while the value at the 95th percentile increased by 2.94, nearly 20 times the increase at the 5th percentile (Supplemental Table 3). Both men and women experienced few changes at the 5th percentile and markedly larger changes at the 95th percentile (Figure 2 and Supplemental Table 3). BMI values at the 95th percentile were higher for women than for men at all median BMI values (Figure 2, Supplemental Table 3). For example, at a mean BMI of 26.9, the 95th percentile for women was 38.8 compared with 34.4 for men (Supplemental Table 2). Furthermore, within each race-ethnic group and each educational level, women had higher BMI values at the 95th percentile than did men (Figures 1 and 2).

QQ plots

The asymmetric changes in BMI levels described previously were evident in QQ plots, which showed that much of the change over time in BMI occurred at higher percentiles of the BMI distribution (**Supplemental Figures 1–3**). For the overall plot (Supplemental Figure 1) and disaggregated by sex, race-ethnicity and educational level (Supplemental Figures 2 and 3), an increasing divergence from the line of equality in all QQ plots over survey years showed growing inequalities in weight gain over time. There was greater divergence from the line of equality above the cutoff for overweight (BMI $\geq$25) and even more deviance above the obese cutoff (BMI $\geq$30).

Sensitivity analyses

Examining the relationship between BMI and height, we found very small associations, ranging between -0.13 and 0.02, which exhibit little change over survey years (**Supplemental Table 4**).

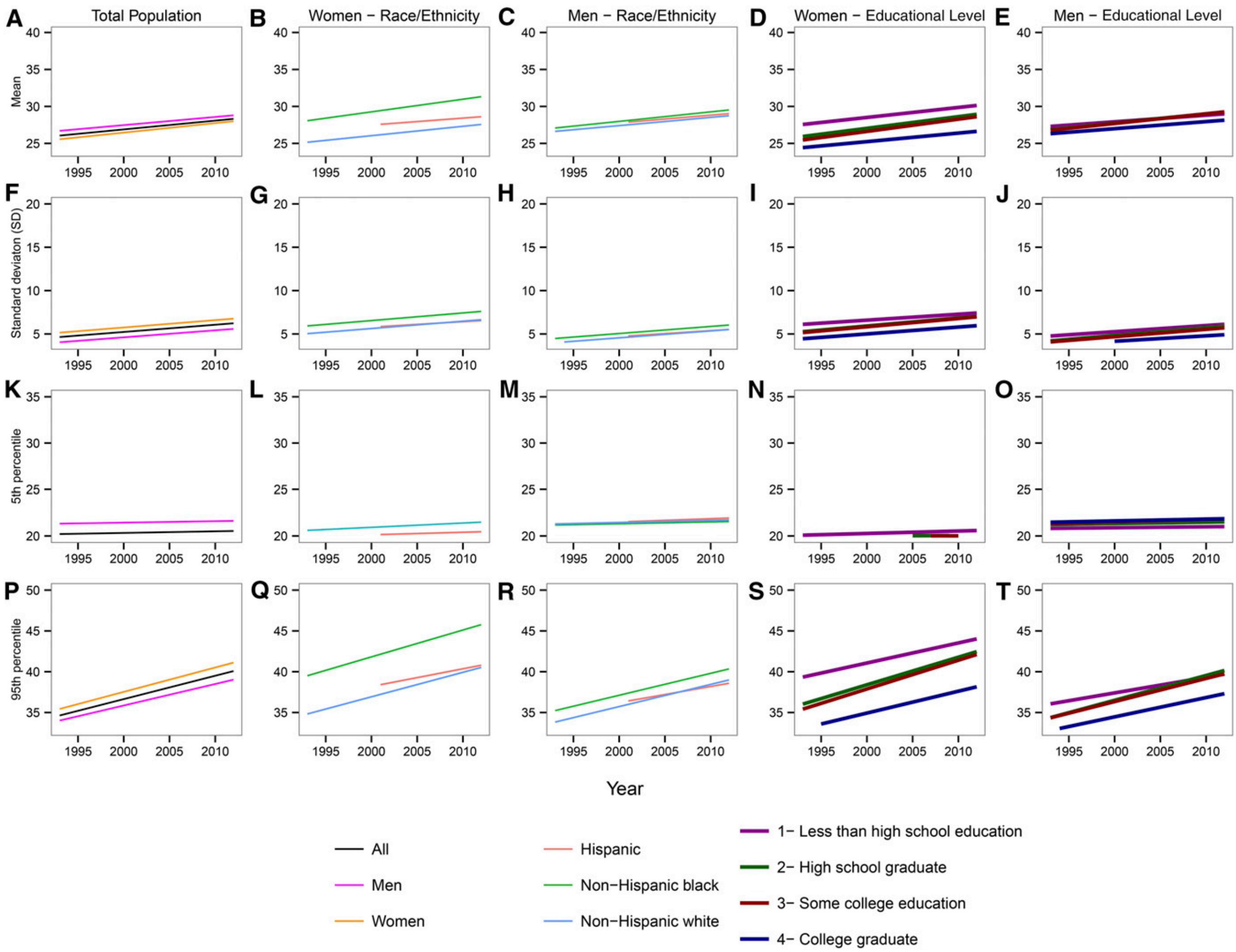

FIGURE 1 BMI (in kg/m^2) distributional variables from 1993 to 2012 for all individuals and by sex, race-ethnicity, and education. For non-Hispanics, data were available from 1993 to 2012. For Hispanics, data were available only from 2001 to 2012. (*n*: all, 3,050,992; women, 1,801,644; men, 1,249,348; non-Hispanic white, 2,604,303; non-Hispanic black, 280,150; Hispanic, 166,539; less than a high school education, 224,619; high school graduate, 876,169; some college, 839,239; college graduate, 1,110,965.)

In manipulating the power of height to find the minimal correlation between BMI and height, we showed the smallest association at $x = 1.4$. In **Supplemental Table 5**, we compared changes in BMI* [computed as weight (kg) divided by height (m) to the power of 1.4] and BMI over survey years, finding similar magnitudes of changes from 1993 to 2012 of 9.1% for mean BMI and 11.8% for mean BMI* for women and 7.5% for mean BMI and 8.7% in mean BMI* for men. Changes in SD of BMI and SD of BMI* were also nearly equal at 31.4% compared with 28.9% for women and 37.5% compared with 35.2% for men. In addition to these parallel changes in BMI and BMI* and small correlations between BMI and height shown in Supplemental Table 2, we also observed similar correlations of nearly 1.0 between mean BMI and mean BMI* and between SD BMI and SD BMI* (**Supplemental Table 6**). These analyses suggested that our findings were robust to changes in height. Our second sensitivity analysis using the coefficient of variation showed that there were still changes in dispersion over time and relative to mean BMI, suggesting that changes in dispersion were independent of changes in mean BMI (**Supplemental Table 7**).

DISCUSSION

Our study of distributional changes in BMI in the United States had 3 important findings. First, increases in mean BMI over time were associated with increasing dispersion in BMI. Second, an increasing spread was related to greater increases in BMI values at the upper tail of the distribution relative to the lower part. Third, stratifying our analysis by sex, race-ethnicity, and educational level showed increasing dispersion within all subgroups, suggesting that group level factors were not driving individual inequalities indicated by increasing dispersion. Our subsequent discussion focuses on potential explanations for increases in individual inequalities and explores implications for current theories of population change.

Several studies have attempted to answer why particular segments of the population are more susceptible to weight gain, leading to increasing inequalities over time. In high-income countries such as the United States, individuals with lower socioeconomic status (SES), i.e., those with lower educational attainment or working in lower grade occupation, are more likely to have higher BMIs than individuals in higher-SES groups (25–

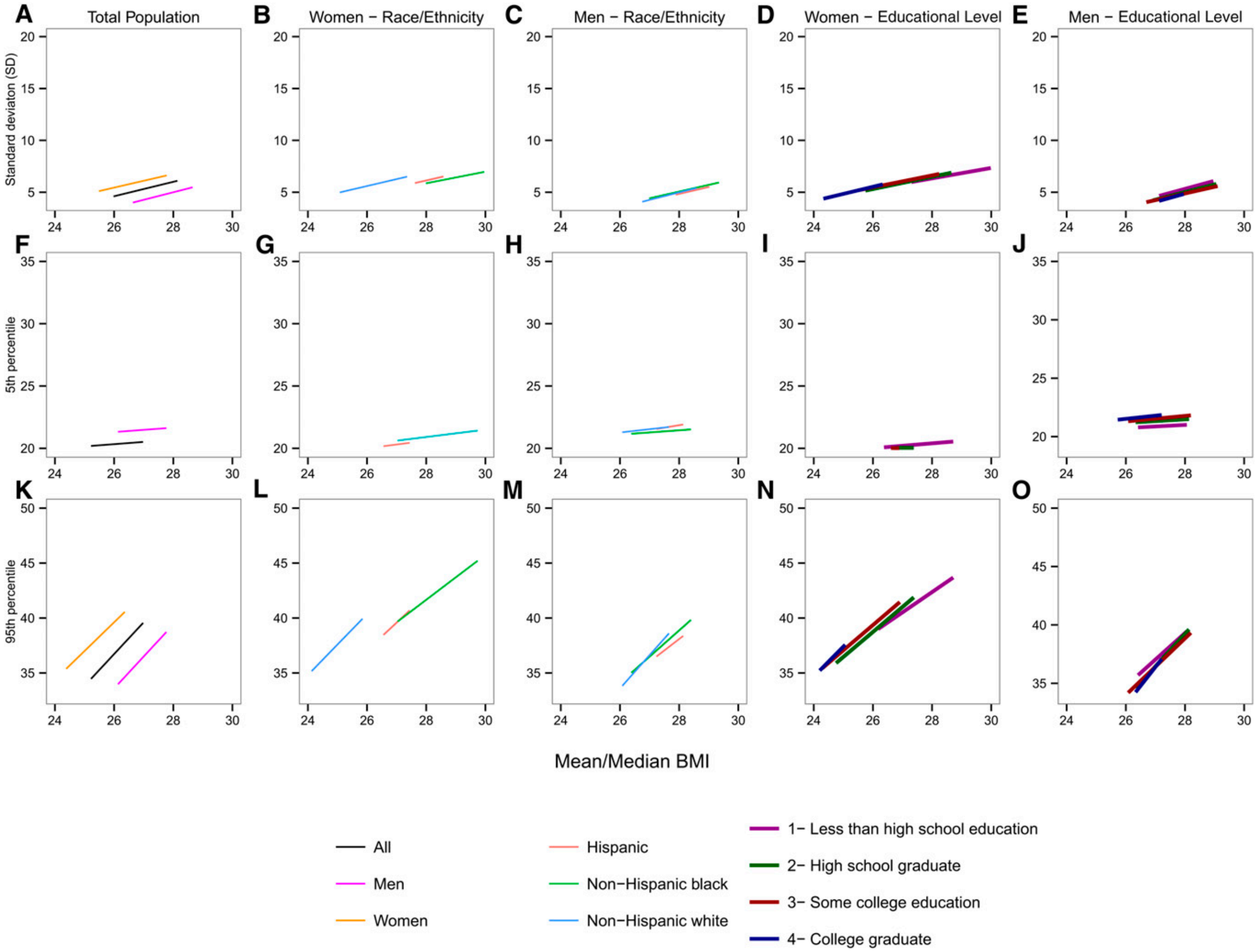

FIGURE 2 BMI (in kg/m^2) distributional variables against the mean or median for all individuals and by sex, race-ethnicity, and education. For the SD of BMI, mean BMI was the independent variable, and for 5th and 95th percentiles of BMI, median BMI was the independent variable. (*n*: all, 3,050,992; women, 1,801,644; men, 1,249,348; non-Hispanic white, 2,604,303; non-Hispanic black, 280,150; Hispanic, 166,539; less than a high school education, 224,619; high school graduate, 876,169; some college, 839,239; college graduate, 1,110,965.)

27). Longitudinal studies showed that both adults and children of low SES are more likely to become obese than those in higher-SES groups, with more-pronounced differences in women (28, 29). However, our findings raise a key question of whether the conventional approach of characterizing population inequalities by differences in mean BMI defined by social groups is sufficient. As the SD increased at the population level over time, it was accompanied by relatively equal increases in the SD within all sex-race-education groups. Growing individual inequalities over time within these subgroups suggested that the increasing population level inequality in weight gain was not solely attributable to socioeconomic or demographic factors, a fact that was not captured by mean group differences. Even if differences between these groups in degree of weight gain partially explain the increasing dispersion in the overall population, there was a more-fundamental effect that drove the increased individual inequalities observed in this study. The finding of increasing dispersion within groups suggested that other causes such as unmeasured social, physiologic, or genetic variables might explain the rising interindividual inequality.

Multiple theories have been proposed to explain increasing dispersion at the individual level. Assortative mating, through which individuals of similar weight are likely to marry one another, may account for some of the variance in BMI between individuals (30). Studies on assortative mating find that phenotypic preferences for similar body weights determine partner selection and propagate the clustering of genetic dispositions for body weight (31–33). However, the current finding of >30% increase in inequalities in weight gain in less than one generation is unprecedented in a high-income country such as the United States and unlikely to have been primarily driven by assortative mating because of the short time frame. Social norms may also drive increasing dispersion by clustering body weights in individuals within groups; however, we showed similar dispersion within social groups. Our findings were confirmed in another study that showed little evidence of a social multiplier effect or within-group clustering on BMI and obesity (34). Others suggested genetic sources of increasing individual-level inequalities. Twin and adoption studies have been used to decompose individual-level variance into genetic and environmental components (35–38). How social disparities, assortative mating, social norms, and genetic predisposition contribute to increasing individual-level inequalities are important areas of future research. Another emerging research area includes the development of predictive models forecasting distributional changes in BMI and changes in rates of obesity on the basis of on increasing dispersion (39).

Although previous work in the United States showed a greater change at the 90th percentile relative to other parts of the distribution (12), greater increases in higher deciles of BMI, and increased variance over birth cohorts from 1882 to 1986 (9), these analyses did not comprehensively address distributional changes in BMI, particularly within socioeconomic and demographic groups. A notable exception was a recent analysis in the United States that showed higher rates of change at upper ends of the BMI distribution in subgroups stratified by sex, race-ethnicity, and socioeconomic status (13). Our study built on this work and comprehensively characterized distributional change in BMI by considering changes at lower and upper ends of the BMI distribution. Our analyses extend a framework that considers increasing dispersion in BMI as a fundamental measure of widening interindividual inequalities and introduce the use of QQ plots as a novel graphical method to reinforce a distributional perspective on population changes in body weight. Furthermore, we showed that these distributional changes occurred within social groups, suggesting that socioeconomic and demographic factors may not explain growing individual inequalities in BMI in the United States.

Comparing our findings to trends outside the United States, in low- and middle-income countries, we determined that changes in mean BMI are also linked to rising individual inequalities in weight gain (40), with increasing inequalities in BMI within countries rather than between countries (41), within rather than between households (42), and for women and children who are at higher ends of the BMI distribution than those at the lower ends (43–46). This finding was also consistent with trends in low- and middle-income countries where increases in mean BMI were accompanied by marked increases in dispersion or inequality (40). Similar trends of increasing individual inequalities were observed in high-income countries in Europe (43, 44).

In addition to increasing dispersion, the higher rate of increase in BMI at the upper tail of the BMI distribution has particular relevance because of the log-linear association of BMI with morbidity and mortality that extended well beyond the obesity threshold of BMI of 30.0 (47). The magnitude of increase in BMI values at the 95th percentile ($>$5.0 over 20 y) was $>$20 times the increase in BMI values at the fifth percentile across all survey years. The rapid increase in BMI at the 95th percentile reflected the increase in extreme levels of obesity in the United States, and was particularly evident for non-Hispanic black women and women with less than a high school education.

This study had a number of limitations. First, cross-sectional surveys allow for the study of changes in the population over time rather than changes within the same individual over time. However, because we were more concerned with population trends, our repeated cross-sectional survey approach using representative surveys allowed us to make inferences at the national level. To our knowledge, there have been no representative surveys of adults in the United States that contained repeated measures on individuals over time. Second, the BRFSS collects self-reported data on height and weight; the NHANES, in comparison, contains measured heights and weights. Using self-reported data for calculating BMI has proven to be problematic, particularly for women who tend to underreport weight (17, 48–51). Contemporaneous comparisons of the NHANES to BRFSS showed estimated prevalence rates of obese and overweight were lower in the BRFSS (2, 4, 17). However, a recent study showed no time trends in self-report bias over NHANES cycles from 1999 to 2008 (52). Thus, the consistent misreporting of weight and height over time greatly lowered the likelihood that the patterns observed in the current study could be explained by the poor quality of data alone. Furthermore, recent work that used different statistical methods and NHANES data to understand distributional changes in BMI showed similar patterns of change (12, 13), thereby reducing the probability that our results were an artifact of self-report bias in the BRFSS. Despite the presence of self-report bias, the use of the BRFSS rather than NHANES had the advantage of a larger sample size. Compared with the NHANES, which pools early survey years, the BRFSS provides yearly surveys to assess annual changes during a period of rapid change in BMI. Third, we were only able to disaggregate information for Hispanics from 2001 onwards, which restricted our full analysis to only 11 y for Hispanics compared with 20 y for non-Hispanic Whites and non-Hispanic blacks. Also, the BRFSS contained small samples of Hispanics for several states in earlier cycles, which led to a lower precision in estimates. Later cycles of the BRFSS contained more information on Hispanics, which led to more-valid inferences for this rapidly growing segment of the US population. Fourth, the BRFSS sampling and weighting have changed over time with the introduction of cell-phone sampling and new raking weights. However, because all BRFSS surveys contain large, representative samples, these changes in sampling and weighting are unlikely to affect our inferences.

In summary, our analysis demonstrates that increases in mean BMI are associated with increasing inequalities in weight gain within different social and demographic groups in the United States. Population variables such as mean BMI or the prevalence of overweight or obese do not adequately capture population-level changes. Further research is required to understand why such rapid increases in dispersion are occurring in a relatively short time interval.

The authors' responsibilities were as follows—AK, FR, and SVS: designed and performed experiments and wrote the first draft of the manuscript; AK, FR, AL, and SVS: analyzed data and contributed reagents, materials, and analysis tools; and AK, FR, AL, GDS, and SVS: contributed to the writing of the manuscript and had primary responsibility for the final content of the manuscript. None of the authors reported a conflict of interest related to the study.

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