The trend of BMI values of US adults by deciles, birth cohorts 1882–1986 stratified by gender and ethnicity

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ABSTRACT

We estimate trends in BMI values by deciles of the US adult population by birth cohorts 1882–1986 stratified by ethnicity and gender. The highest decile increased by some 18–22 BMI units in the course of the century while the lowest ones increased by merely 1–3 BMI units. For example, a typical African American woman in the 10th percentile and 64 in. (162.6 cm) tall increased in weight by just 12 pounds (5 kg) whereas in the 90th percentile her weight would have increased by 128 pounds (58 kg). Hence, the BMI distribution became increasingly right skewed as the distance between the deciles increased considerably. The rate of change of the BMI decile curves varied greatly over time and across gender and ethnicity. The BMI deciles of white men and women experienced upswings after the two world wars and downswings during the Great Depression and also decelerated after 1970. However, among African Americans the pattern is different during the first half of the century with men's rate of increase in BMI values decreasing substantially and that of females remaining constant at a relatively high level until the Second World War. After the war, though, the rate of change of BMI values of blacks came to resemble that of whites with an accelerating phase followed by a slowdown around the 1970s.

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1. Introduction

Descriptive statistics pertaining to the dramatic increase in the prevalence of overweight and obesity among the US population have been reported extensively; (Ogden et al., 2004, 2008, 2010; Flegal et al., 1998, 2010) however, identifying the onset of the increase in BMI values has remained rather elusive. Most studies imply that the phenomenon appeared rather suddenly in the 1980s. Perhaps Troiano and Flegal (1998) reflect the typical view most succinctly by suggesting that "Overweight prevalence increased over time, with the largest increase between NHANES II and NHANES III," surveys, that is to say, in the 1980s (Anderson et al., 2003; Rashad et al., 2006).[1] Moreover, as dozens of other studies, Ogden et al. (2006) point out that "between 1980 and 2002, obesity prevalence doubled in adults aged 20 years or older."[2] Nonetheless, in our view such snapshots do not result in an accurate depiction of trends.[3]

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[1] The upswing in excess weight is said to have begun in Australia in the 1970s (Norton et al., 2006). It is also seldom mentioned that the BMI values in the US are among the highest in the developed world (Komlos and Baur, 2004).

[2] See also http://www.cdc.gov/nchs/data/hestat/overweight/overweight_adult.htm.

[3] Even if the Center for Disease Control reports age-adjusted distributions.

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The reason for the ambiguity is that the conventional views refer only to period effects (measurement years) rather than to birth-cohort effects. Insofar as it is not at all evident from cross-sectional evidence when the measured weight status was actually reached, the focus on period effects does not lead to convincing trend estimates as the weight gains could have accumulated at any time between birth and the moment of measurement.

Thus, BMI values obtained at the time when the surveys were conducted do not convey all the information necessary to analyze trends and to devise appropriate policy to address the problems at hand. For instance, the estimates might well mislead policymakers into thinking that earlier technological developments, such as the introduction of automobiles and radios in the 1920s and television in the 1950s, were not associated with the sudden rise in obesity in the 1980s. However, forming hypotheses about possible causal links are useful in devising policies to respond to the current developments. The policy implications are also different if the development started 30 years ago than if they began much earlier, inasmuch as longer processes are presumably ingrained deeper into the cultural and socio-economic fabric of a society and therefore a much more comprehensive policy is needed in order to thwart and reverse the trend.

A good example of the effect of the biases of the conventional trend estimates on an immediate practical level is related to the construction of weight reference charts for the US. The belief that the acceleration in body mass started in the 1980s led the Center for Disease Control to base their US weight standards for children mostly on the surveys of the 1960s and 1970s. However, if the gains in weight among children were already underway by then, then the reference charts currently being used clinically would be actually quite biased and misleading (Komlos et al., 2009). This would have severe implications insofar as many children who are in fact overweight would fall into the chart's normal range and they (and parents) would be consequently misled into complacency about their diet and physical activity.

Hence, in contrast to the most common method, we estimate trends by birth cohorts. The birth cohort estimates have some advantages insofar as social, economic, cultural and technological experiences of birth cohorts are more homogeneous than those of period cohorts. These experiences would have affected their life style, physical activity and food consumption more uniformly than that of measurement cohorts whose experiences were more heterogeneous with respect to the above independent variables. For example, those measured in 1960 were exposed to television viewing for different lengths of time during their lives and therefore one would expect TV to have had a more varied impact on the weight (and body mass) of the population sampled in 1960. In contrast, all those born in 1960 have had access to TV viewing all their lives, regardless of when they were measured. Hence, the impact of this new technology was more uniform on birth cohorts than on measurement-year cohorts. Yet another reason to consider birth cohorts is that lifestyle habits and weight status acquired early in childhood tend to persist into adulthood (Freedman et al., 2005).

In sum, while period effects provide the upper bound for the time when the measured weight level was reached, birth-cohort effects provide the lower bound. Thus, neither approach is perfect, but in the absence of longitudinal data both have a legitimate place in scientific inquiry, even if neither approach is fully specified because of colinearity (period – age = cohort). To be sure, for some policy considerations one might well be interested primarily in the current BMI distribution. For example, in order to plan for the current demand for medicine and medical services related to the adverse effects of obesity one would be primarily interested in the current distribution of BMI values. However, in order to understand the relationship between technological change and the long-run evolution of BMI values the birth cohort approach provides some advantages such as the uniformity of technological experiences of a cohort (Komlos and Brabec, 2010). Another considerable advantage of the birth-cohort perspective is that instead of having only a handful of data points from the cross-sectional surveys about to be analyzed (1959–2006), from which a few differences can be calculated, we obtain data continuously for the 105 years 1882–1986,[4] enabling us to calculate the annual rate of change of BMI deciles.

Analyzing the evolution of the BMI distributions by deciles instead of by central tendencies alone has advantages inasmuch as it provides a comprehensive view of the evolution of the shape of the distribution. It enables one to chart the trends in BMI values among different deciles of population. The distribution was considerably distorted over time implying that some segments of the society were immune to gaining weight while others were excessively prone to it. Gaining a better understanding of the shifts in the shape of the distribution should enable us to gain insights into how various segments of the population experienced the pressures of an obesogenic environment and thereby to improve the chances of formulating appropriate policies to counter the trend in the future.

2. Historical excursion

There is ample evidence that the roots of the obesity pandemic do reach much further back in time than is commonly asserted (Carson, 2009; Cuff, 1993; Coclanis and Komlos, 1995; Komlos, 1987). Even Flegal et al. (2002, p. 1724) recognize even if in passing, that recent developments "may also be viewed as part of a longer-term trend for increases in body size in affluent and well-nourished societies." They infer from the first national survey that the rate of prevalence must have increased earlier: "Even as long ago as 1960, almost 50% of men and more than 40% of women were overweight, and 11% of men and 16% of women were obese" (p. 1727).

One can also infer from scattered archival evidence gleaned from prisons and military schools that BMI values must have been increasing much earlier than the prevailing view would have it. Human weights were not routinely

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[4] NHANES continuous is counted in this regard as one survey insofar as the number of observations 1999–2006 is similar to that of NHANES III.
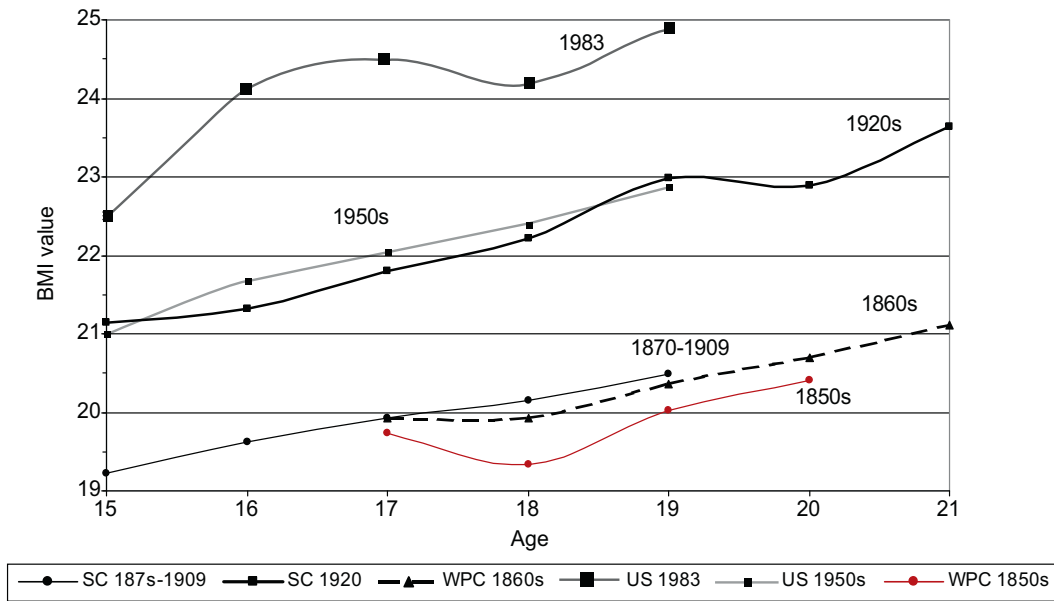
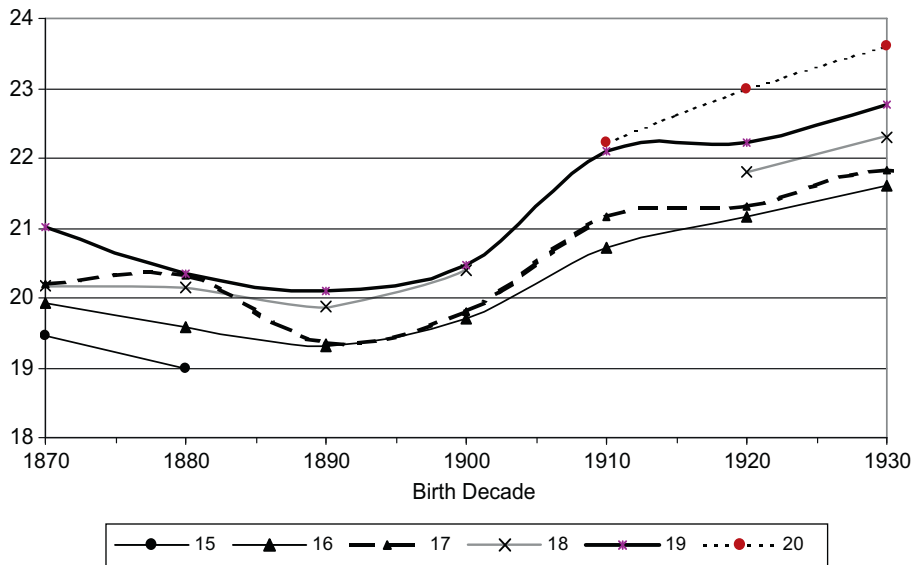Fig. 1. BMI values of US-born white male youth, born c. 1850–1983.

Fig. 2. BMI values of students attending The Citadel Military Academy in Charleston, SC.

recorded until the second half of the 19th century. The West Point Military Academy was among the first to record the weights of entrants beginning with the 1870s. Although obviously not representative of the population at large, such glimpses do, nonetheless, enable us to gain valuable insights into trends among this elite group.

These data reveal that by today's standards the average BMI values were amazingly low in the 19th century, with many underweight cadets. Furthermore, BMI values did not increase at all during the second half of the 19th century even among military cadets who were surely among the better situated members of the society (Fig. 1). For instance, 19-year-old cadets had an average BMI value of c. 20.5 i.e., about the 18th percentile of today's standard

(Cuff, 1993; Hiermeyer, 2010; Komlos, 1987). In contrast, today's reference value of 20 year old females is 21.7. About 90% of the cadets were below today's median reference value and 14% would be classified today as underweight. Another regional sample from The Citadel military academy in Charleston, S.C., indicates similarly that BMI values were extremely low and continued to be so for the remainder of the 19th century (Fig. 2). In fact, BMI values actually tended to decline slightly toward the turn of the 20th century.[5] However, these data indicate a

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[5] Evidence from the military corroborates the decline in BMI values toward the end of the 19th century (Costa and Steckel, 1997, p. 55).
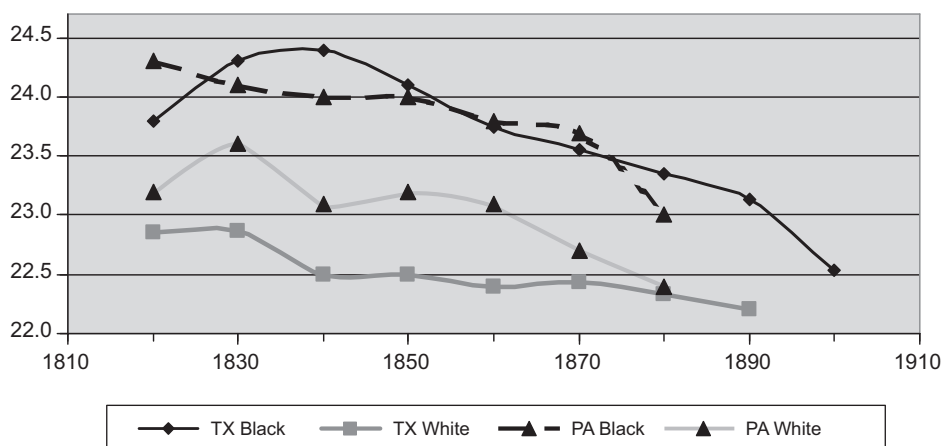
Fig. 3. Trend in BMI values of men in Texas and Pennsylvania, born in the 19th century.
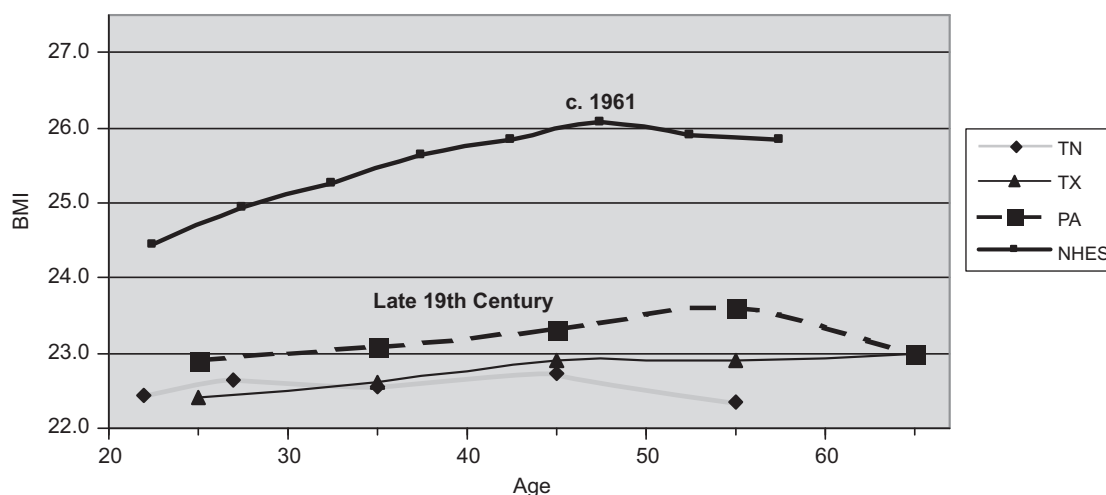Source: Carson, 2008, 2009.

Fig. 4. BMI values of USA white men by age.
Sources: Carson (2008, 2009), Sunder (2004), NHES.

true surge in BMI values (of some 2.5 points) among those born in the 1920s (Coclanis and Komlos, 1995). This is the first indication that the beginning of the transition to postindustrial BMI values had begun. Note that 18-year-old men increased by some 13 kg (28.5 pounds) during the course of the 20th century but about half of the increase took place among those born before World War II. Hence, these data indicate that a considerable increase in weight had already taken place by the time the first national survey was taken in 1959–1962.

Data on adults suggest a similar pattern: mean BMI values were in the normal range of about 23 at the middle of the 19th century (Bodenhorn, 2010a,b). Their weight was also possibly declining slightly among cohorts born toward the end of the century[6] (Fig. 3). BMI values obtained from Texas, Pennsylvania, and Tennessee prison samples as well as from Union Army soldiers were all well below those

obtained in the first national health survey (Fig. 4) (Costa, 2004, p. 14; Sunder, 2004; NHES, 1959–1962). So were the BMI values of Union Army veterans even though they were older by the turn of the 20th century (Helmchen and Henderson, 2004). In contrast to BMI values around 22.5 among white convicts (Carson, 2009), and 23 among Union Army soldiers, the mean value measured c. 1960 was closer to 25.5, a substantial increase of some 3.0 BMI units or about 0.5 units per decade (Fig. 4). Note that the rate of increase during the next four decades was faster at about 0.7 BMI units per decade, but not much faster. Though blacks tended to have higher BMI values, they experienced a similar rise in BMI values during the first half of the 20th century (Fig. 5). Furthermore, the prevalence of obesity was merely 1.4–1.6% in the early 20th century (Carson, 2009), but by 1960 it had reached some 11% (Flegal et al., 2002, p. 1727). These data suggest consistently that a substantial increase in BMI values had already taken place by the time of the first national sample c. 1961, and thereby contradict the conventional wisdom that US weight gains began suddenly in the 1980s. To be sure, the initial increases in BMI values

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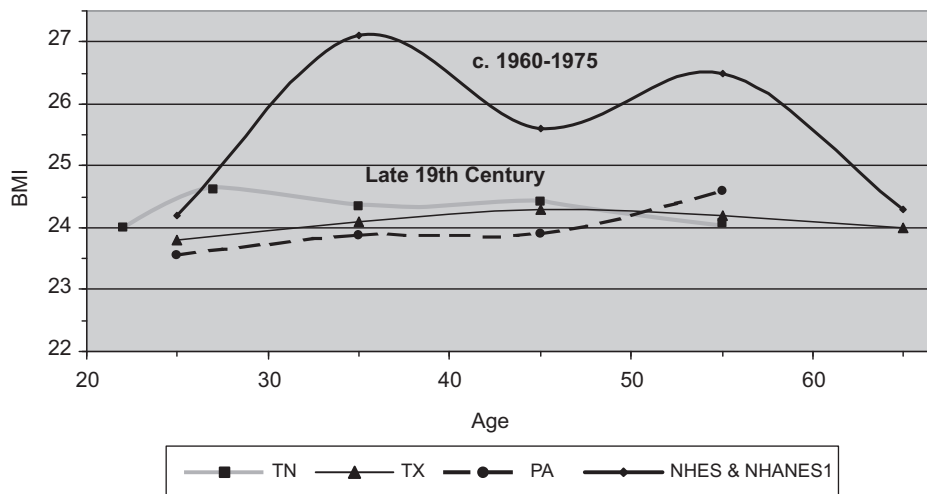[6] Furthermore, black BMI values were above that of whites.

Fig. 5. BMI values of USA black men by age.
Sources: Carson (2008, 2009), Sunder (2004), NHES, NHANES 1.

were modest until the 1920s and most of the population's weight remained within the healthy range; this helps to explain why the creeping trend tended to be overlooked or disregarded.[7] While any generalization based on such scattered regionally and socially limited evidence needs to be considered as tentative, they do suggest uniformly that the transition to postindustrial BMI values most probably began well before the Second World War (Komlos et al., 2009).

Moreover, several studies chose new approaches recently in the analysis of obesity trends which, too, contradict the prevailing opinion. Burkhauser et al. (2009) analyzed an alternative measure of obesity (skin-fold thickness) and infer that an increase in obesity is already evident among cohorts measured in the 1970s, that is to say, earlier than generally supposed. Komlos et al. (2009, p. 158), using birth cohorts to analyze trends in children's BMI values, conclude that "it appears highly unlikely that the obesity pandemic appeared suddenly in the 1980s among American children as conventional analysis would suggest...but has rather manifested itself slowly and persistently for an extended period of time". Furthermore, Komlos and Brabec (2010) estimated the trend in the mean BMI values of US-born adults by birth cohorts to find that they have been increasing continuously throughout the 20th century. This "creeping" nature of the trend is quite contrary to the received wisdom which tends to place the onset of the acceleration in the prevalence of obesity in the final decades of the 20th century. The only other published study using birth-cohort trends finds that cohort effects were indeed substantial, although Reither et al. (2009) infer that the significance of such effects declined during the first half of the 20th century. They also

find that the probability of being obese increased among the cohorts born after 1955, and that they were particularly rapid among black women, increasing by some 62% between the birth cohorts of 1955 and 1975. Our current aim is to expand the results in Komlos and Brabec (2010), which focus exclusively on mean BMI values, by estimating trends by deciles for four categories of adults, for whites and blacks by gender using all the NHES and NHANES data sets collected between 1959 and 2006.

3. Data and method

Against this historical backdrop we estimate for the first time by deciles the long-term trends in the BMI values (kg/m^2) of adults continuously for the birth cohorts 1882–1986 stratified by gender and ethnicity on the basis of surveys collected between 1959 and 2006 by the National Center for Health Statistics (NCHS). We concatenate all the National Health Examination and National Health and Nutrition Examination Surveys.[8] We use the medical examination survey weights for all the statistical models. We calculate them according to the formula given in Korn and Graubard (1999)[9] and use these weights throughout the analysis.[10] We limit the analysis to US-born adults – above the age of 19 – (white male, white female, black

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[7] Another important pattern in the historical record is that the pronounced increase in BMI values with age in today's population scarcely existed in the 19th century (Figs. 4 and 5). The average BMI value of Union Army soldiers rose a mere 1.3 points, from 21.8 to about 23.1, by the time they retired (Gould, 1869; Helmchen and Henderson, 2004).

[8] National Health Examination Surveys: (NHES I: 1959–62), and the National Health and Nutrition Examination Surveys: (NHANES I: 1970–75, NHANES II: 1976–80, NHANES III: 1988–94, and Current NHANES 1999–2006). Heights and weights in the surveys are actual measurements. Four surveys were conducted between 1959 and 1994 and another 4 between 1999 and 2006. Because the latter 4, composing the current NHANES, were so close in time and because the number of observations is smaller, we consider the current NHANES as one survey, making a total of 5 effective surveys.

[9] The survey weights were recalculated separately for the four ethnic/gender combinations using formula 8.2–4 (p. 282).

[10] The NHANES/NHES sample is post-stratified by age. Therefore the sample weights are representative of the age structure of the population. That means that the sample should also be representative by birth cohorts as well.

male, and black female are fitted separately). In order to ensure comparability over time and to reduce uncontrolled heterogeneity (Rosenbaum, 2005) (through immigration, for example) we exclude Hispanics from the analysis.[11] (For the sake of brevity we drop the designation non-Hispanic in reference to non-Hispanic whites or non-Hispanic blacks.) (N = 4976 black women, 14,083 white women, 4135 black men, and 12,651 white men).[12]

For modeling the BMI distribution and its dependence on several covariates, we use the approach based on the generalized additive model for location, scale, and shape (GAMLSS), developed by Rigby and Stasinopoulos (2005, 2006, 2007). This can be seen as a generalization of the generalized linear model (GLM) (McCullagh and Nelder, 1989), as well as of the generalized additive model (GAM) (Hastie and Tibshirani, 1990), or even of the LMS[13] approach (Cole, 1988). The advantage of GAMLSS is that it enables one to fit not only the mean of the distribution as a function of the covariates, as is usual in linear, nonlinear, or nonparametric regression, but also other characteristics. Similarly as in GAM, variability can be modeled in detail as well. Yet, in GAMLSS, the modeling is more flexible as it allows other moments (i.e., skewness and kurtosis) to change with the covariates. This is necessary if one is interested in a realistic and flexible description of the whole BMI distribution and its changes with several explanatory variables. The distribution itself can be characterized by deciles and their changes over the range of the selected covariates. Because this is our aim, we need to allow for departures from normality and for estimation of several characteristics of the distribution simultaneously: i.e., mean, variability, skewness, and kurtosis.

In particular, after some experimentation, we model the BMI distribution using the Box–Cox t family, BCT(μ, σ, ν, τ) (Rigby and Stasinopoulos, 2006). This is a parametric but flexible family of distributions having parameters μ, σ, ν, τ. Variable Y with positive ($\Re^+$) support[14] has the BCT(μ, σ, ν, τ) distribution if the transformed variable Z has the following form:

$$Z = \frac{1}{\sigma\nu}\left[\left(\frac{Y}{\mu}\right)^\nu - 1\right], \quad \text{if } \nu \neq 0$$
$$= \frac{1}{\sigma}\log\left(\frac{Y}{\mu}\right), \quad \text{if } \nu = 0 \tag{1}$$

Z is a truncated standard t distribution with τ degrees of freedom (where $\tau > 0$ does not need to be an integer). Truncation at zero is induced by the positivity of Y. In our case, the amount of truncation is very small. Under such circumstances, μ can be interpreted approximately as the median of Y, σ as the interquartile-range-based coefficient of variation as a measure of relative variability,[15] ν controls skewness, and τ controls kurtosis, or just how heavy the tails of Y are (Rigby and Stasinopoulos, 2006).

Our model allows the BCT(μ, σ, ν, τ)'s parameters to change with the covariates in a flexible, nonparametric way. Specifically, we use the cubic spline family (Eubank, 1988; Green and Silverman, 1994; Rigby and Stasinopoulos, 2007) to model dependence of μ, σ, ν and τ on covariates. We model the link-transformed[16] parameter as cubic splines in continuous variables plus effects of factors in the ANOVA style (Graybill, 1976; Rawlings, 1988) for discrete variable coding of the education level of a particular person. We use identity link for μ, ν and log link for σ, τ parameters and model $\mu, \nu, \log(\sigma)$ and $\log(\tau)$ by cubic splines. We also assume independence among individual responses. Strictly speaking, this does not reflect the clustering induced by the survey sampling design used in NHANES data, but we use this as a reasonable approximation.

Thus, our model is described by the following equations:

$$\text{BMI}_i \sim \text{BCT}(\mu_i, \sigma_i, \nu_i, \tau_i) \tag{2}$$

$$\mu_i = cs_\mu(\text{Age}_i, 4) + cs_\mu(\text{Birth\_yr}_i, 5) + cs_\mu(\text{PIR}_i, 2)$$
$$+ \sum_{m=1}^{3} \alpha_{\mu m} I(E_i = m)$$

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[11] The US-born criterion cannot be applied to NHES I. For NHES II and III we assume that those with a birth certificate were US-born. Information on Hispanic ethnicity is available only for NHANES III and Current NHANES. Lack of information in earlier surveys does not constitute a major problem, though, inasmuch as Hispanics were not oversampled before NHANES III and they constituted a smaller share of the population at the time. This aspect of the surveys arguably added a negligible error to the measurements.

[12] About 4–5% of individuals with missing values are excluded from the analysis. The number of observations among whites both men and women is miniscule before 1900 but rises quickly until 1910 to reach close to 200 per annum and stays at that level until c. 1960 and then begins to decline rapidly thereafter. Among blacks the N's rise linearly between 1900 and 1950 to reach about 90 per annum and then declines linearly thereafter.

[13] The LMS method is a Box–Cox transformation-based spline smoothing with which median, coefficient of variation, and Box–Cox transformation parameter are modeled as smooth functions of a covariate, using splines.

[14] Support is the closure of a set where the density of the random variable of interest is positive.

[15] Sigma is related to the coefficient of variation, CV. Rigby and Stasinopoulos (2006) derive the following approximate formula: $CV \approx \sigma[1 + 0.36/\tau]$. Nevertheless, the coefficient of variation is defined somewhat differently from what is used normally. Usually, one uses CV = std . deviation/mean. Here, one uses the so-called decile-based coefficient of variation, namely CV = 3.IQR/4.median, where $IQR = Q_3 - Q_1$, interquartile range is the difference between third and first quartiles of the distribution. One can consider it just another way of computing CV as a measure of relative variability, in which the mean is replaced by median and standard deviation by (appropriately scaled) interquartile range. The factor of comes from the fact that under normality, one needs such scaling to have an unbiased estimate of the standard deviation. In fact, under normality, to have unbiasedness, $\hat{\sigma} \cong 1.4826$ MAD = $(1.4826 IQR/2) \cong (3/4) IQR$.

[16] As in the case of the generalized linear models (McCullagh and Nelder, 1989), here we deal with a model that is inherently nonlinear (in parameters). It is of relatively tame nonlinear class, however. Specifically, the linear predictor (i.e., linear combination of covariates or explanatory variables with unknown coefficients as parameters) does not model the μ, σ, ν or τ directly. Instead, it models its one-to-one function. The function is called a link.
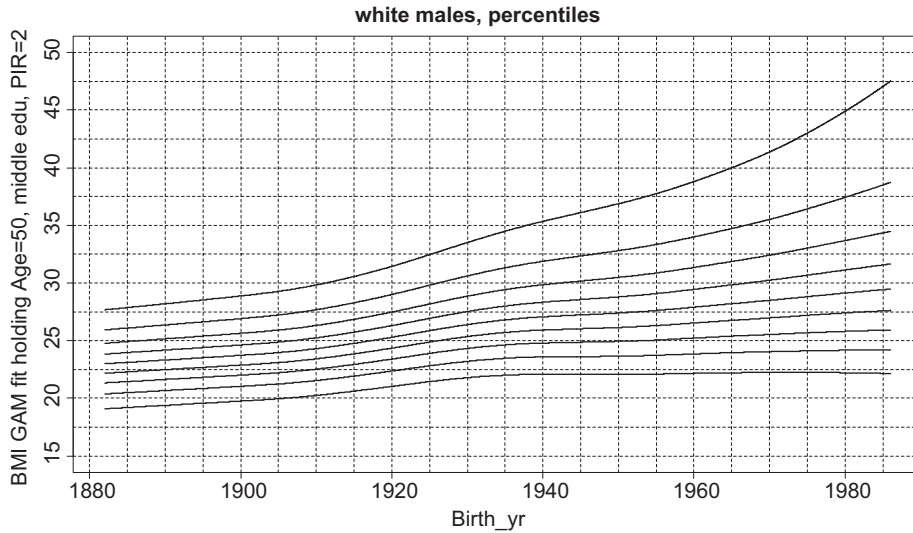
white males, percentiles

Fig. 6. Trend of BMI decile curves of US-born white men by birth cohorts. *Note*: All figures show model (2) estimates evaluated at PIR = 2 at age 50 and with a High School Diploma.
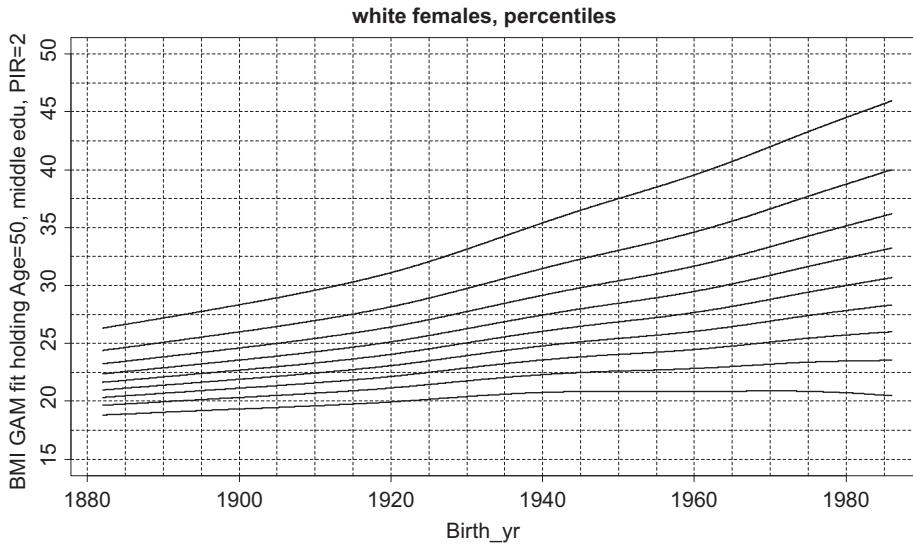
white females, percentiles

Fig. 7. Trend of BMI decile curves of US-born white women by birth cohorts.

$$\log(\sigma_i) = cs_\sigma(\text{Age}_i, 1) + cs_\sigma(\text{Birth\_yr}_i, 2) + cs_\sigma(\text{PIR}_i, 1)$$

$$+ \sum_{m=1}^{3} \alpha_{\sigma m} I(E_i = m)$$

$$\nu_i = cs_\nu(\text{Age}_i, 1) + cs_\nu(\text{Birth\_yr}_i, 1) + cs_\nu(\text{PIR}_i, 1)$$

$$+ \sum_{m=1}^{3} \alpha_{\nu m} I(E_i = m)$$

$$\log(\tau_i) = cs_\tau(\text{PIR}_i, 1),$$

where $I(\cdot)$ is the indicator function which equals 1 if the condition in its argument is true, and 0 otherwise. E_i is the level of education of the subject. $cs(x, d)$ is the cubic spline

in a variable x with d degrees of freedom.[17] BMI_i is the BMI for the ith person. Similarly, Age_i is the age in years, Birth_yr_i is the birth year, PIR_i is the Poverty Income Ratio for the ith person.

μ, σ, ν, τ change from individual to individual, but only through changes in various covariates. Unlike the others, τ changes only with a single covariate, PIR. Nevertheless, both spline parts involved in $\mu_i, \sigma_i, \nu_i, \tau_i$ as well as in the educational effects $\alpha_{\mu m}, \alpha_{\sigma m}, \alpha_{\nu m}, m = 1, 2, 3$ are (simultaneously) estimated via the Rigby and Stasinopou-

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[17] d's were selected separately for each cubic spline term in the model (1), based on the GAIC criterion described on the next page. Generally, the larger is the degree of freedom for a spline, the less smooth and more complex the spline function is.
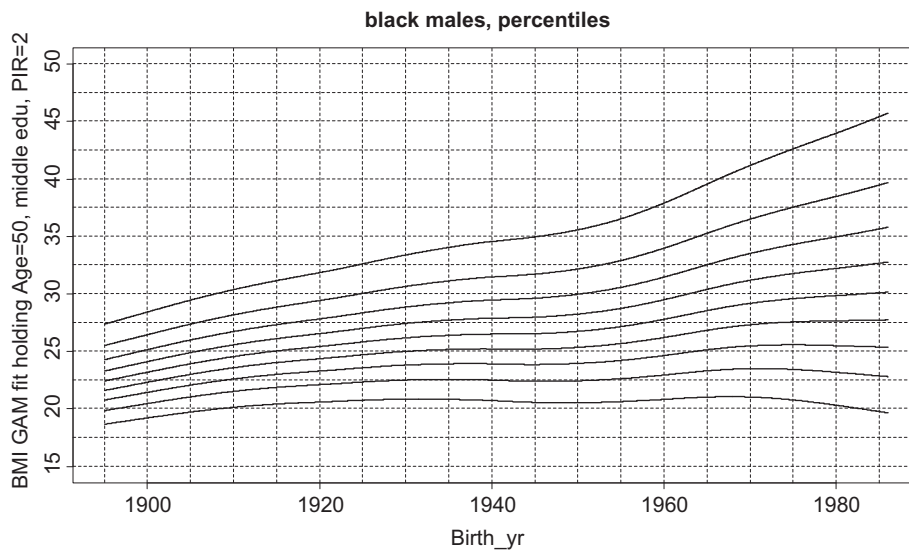
black males, percentiles

Fig. 8. Trend of BMI decile curves of US-born black men by birth cohorts.

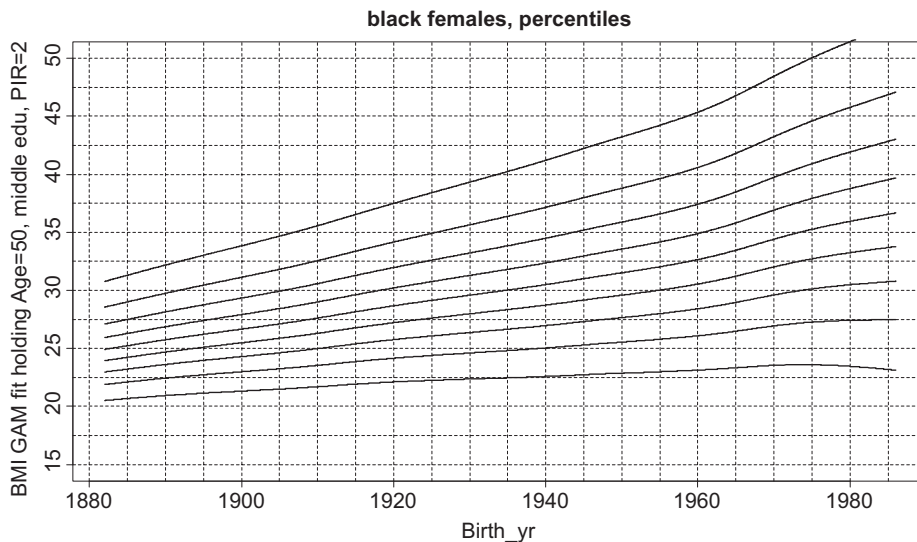**black females, percentiles**

Fig. 9. Trend of BMI decile curves of US-born black women by birth cohorts.

los (2005) algorithm from the data. In particular, they are not assumed a priori as they would be if, for example, one would assume normality.

The degrees of freedom for splines in various variables are very important in that they control the smoothness of the fit. Therefore, they ought not to be set arbitrarily. Instead, they were selected using GAIC, or generalized Akaike information criterion (Rigby and Stasinopoulos, 2005). Only integer values of the degrees of freedom were considered in the search. Compared to the model of Komlos and Brabec (2010), model (2) allows different smoothness in different variables as well as different smoothness in the same explanatory variables for different characteristics, e.g. $cs_\mu(\text{Age}_i, 4)$ and $cs_\sigma(\text{Age}_i, 1)$. Note that generally, for more complicated characteristics (from μ to τ), the curves are less complex (basically smoother), as expected.

We show the results of the weighted analyses.[18] Computations are done using the GAMLSS package (Rigby and Stasinopoulos, 2007) from the "R" software environment (R, 2010), together with some additional code written by us.[19] Individuals with missing values for any of the variables were excluded from the estimation.[20] Although we control for income, education, and age, we do

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[18] The shape of the decile curves does not change substantially if we recompute the model with the unweighted data, however.

[19] In particular, we do not use the deciles function built into the GAMLSS package, because we have several covariates in the model.

[20] We explored the model fit by means of decile residuals considering various plots, similar to those used in standard regression, e.g., residuals vs. fitted, Q–Q plots, histograms of residuals, and also at worm plots (van Buuren and Fredriks, 2001).

Fig. 10. Variability of BMI values over time, the σ function by sex and ethnic groups.
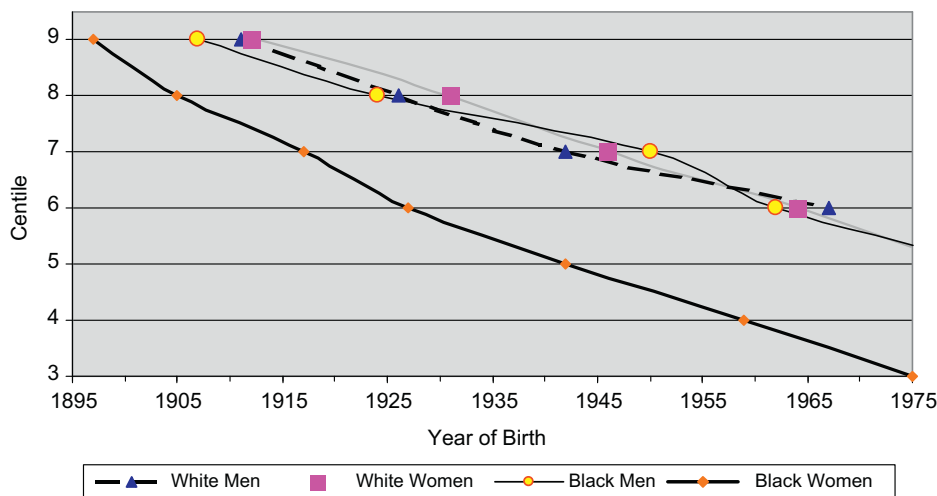

Fig. 11. Dates at which a particular decile reached a mean BMI value of 30.
Source: Table 1. *Note*: Among white men and women, and black men, the 5th, 4th and 3rd deciles have not reached the BMI value of 30 during the observation period.

not report these results here for lack of space and inasmuch as these are not particularly different from those reported in Komlos and Brabec (2010).

4. Results

That the persistent increase in BMI values was already underway among the birth cohorts of the late 19th century is confirmed by these estimates in all four groups (Figs. 6–9). There are a number of similarities and differences in the experience of the four groups considered. They are quite similar in that the shapes traced out by the BMI deciles can be characterized as practically having a shape of a half-fan in the sense that the upper deciles rotate up as the ridges of a fan while the lower ones remain essentially unchanged.

Table 1
Dates at which a particular decile reached a mean BMI value of 30.

()	White		Black	
Decile	Males	Females	Males	Females
9th	1911	1912	1907	1897
8th	1926	1931	1924	1905
7th	1942	1946	1950	1917
6th	1967	1964	1962	1927
5th	na	1980	1982	1942
4th	na	na	na	1959

Note: Dates refer to birth cohorts. Among white men and women, and black men, the 5th, 4th and 3rd deciles have not reached the BMI value of 30 during the observation period.
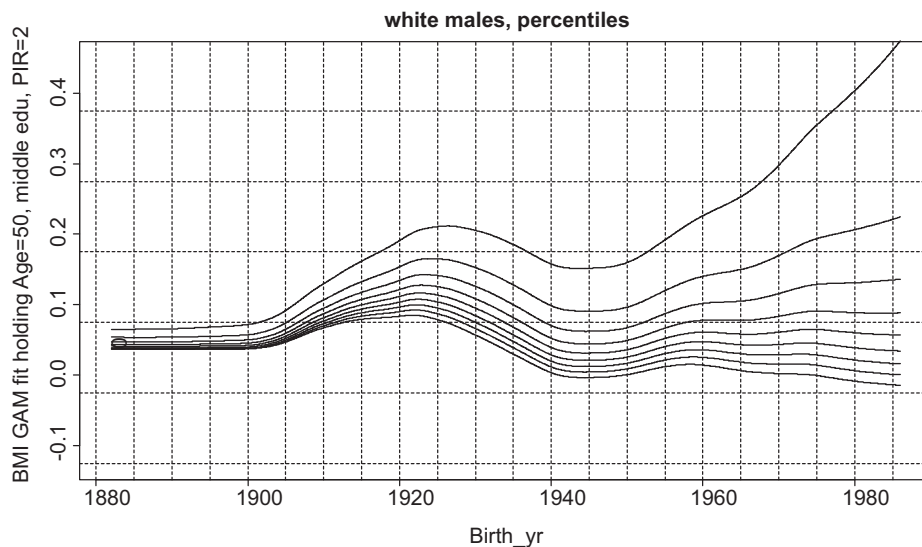
Fig. 12. Rate of change of BMI decile curves of white men by birth cohort in Fig. 6.
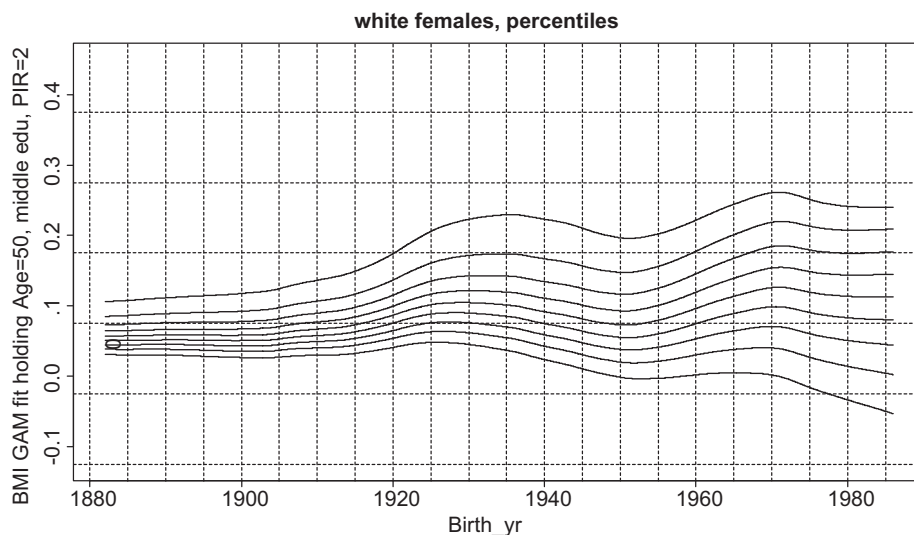

Fig. 13. Rate of change of BMI decile curves of white females by birth cohort in Fig. 7.

Consider that the highest deciles increased by some 20, 20, 18, and 22 units (WM, WF, BM, BF) during the period under consideration while the lowest ones increased by merely 3, 1.5, 1, and 2 units. This implies that the distribution did not shift out uniformly. Its shape has been deformed considerably and continuously so that it has become extremely skewed to the right.

Another way of describing this pattern is to consider the variation across the deciles. These also indicate that the variance increased continuously as the deciles rotated upward (Fig. 10). Obviously, the increase in variance is accompanied by a substantial skewing of the distribution toward the more obese range, rather than by a uniform increase in the whole BMI spectrum. One can also consider,

moreover, the deciles of birth cohorts which reached 30 units of BMI, the conventional definition of obesity, as a measure of this upward rotation (Table 1 and Fig. 11). The rate of rotation was rather similar among white males and females, and black males. However, black females were often 30–40 years ahead of the other three groups in reaching the level of obesity in a particular decile.

5. Rate of change of percentile curves

The rate of change of BMI decile curves was calculated by numerical differentiation of the decile functions estimated by model (2) with respect to the time of birth. These varied substantially over time in all four groups
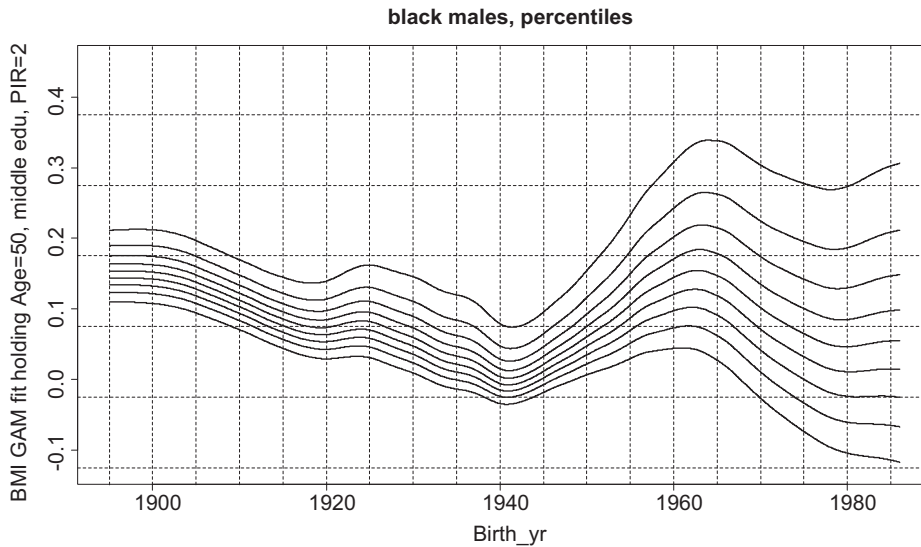
black males, percentiles

Fig. 14. Rate of change of BMI decile curves of black men by birth cohort in Fig. 8.
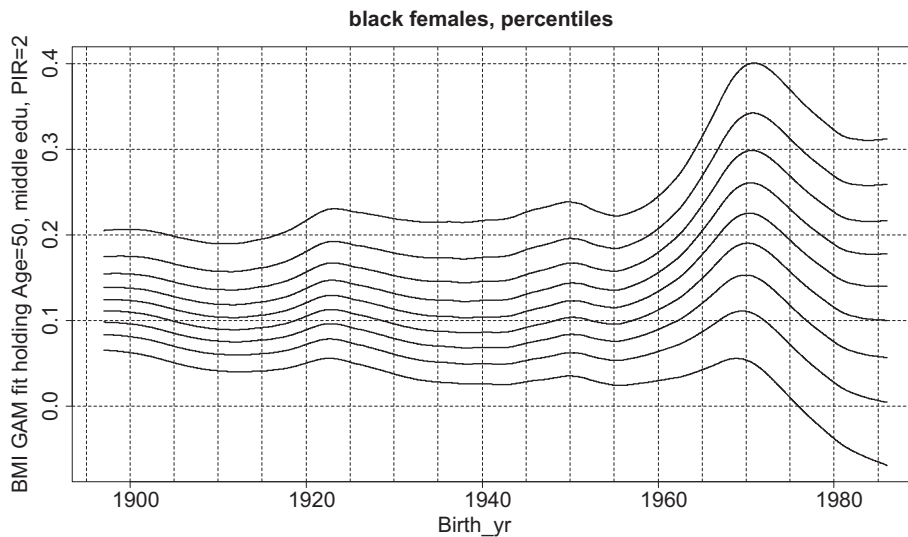
black females, percentiles

Fig. 15. Rate of change of BMI decile curves of black females by birth cohort in Fig. 9.

under study (Figs. 12–15). Initially, the rate of change was lowest among white men born in the 19th century and remained constant until the turn of the 20th century. This was followed by a rapid acceleration in BMI values around World War I accompanied by a marked divergence between the lower and upper deciles that continued for the remainder of the century, leading to a substantial increase in skewness of the BMI distribution. However, the rate of change peaked in the mid-1920s and decelerated during the Great Depression, reaching a nadir during the Second World War (Fig. 12). During the war the rate of change among white men was still positive in most of the deciles, though at the lower deciles the rate dipped below

that experienced in the late 19th century. However, in the upper deciles the rate was well above those of the 19th century even during the war. Another turning point was reached in the early 1950s as BMI values accelerated once again similarly to the pattern obtained after the First World War. Yet, the second upswing in the lower deciles was both considerably shallower than the first one and reached a plateau quickly in the 1950s. By the birth cohorts of the early 1960s the rate of change of BMI values was constant or even negative among the lower deciles. Only in the higher deciles did the acceleration persist until the present day and pass the previous peak reached in the mid-1920s (Fig. 12).
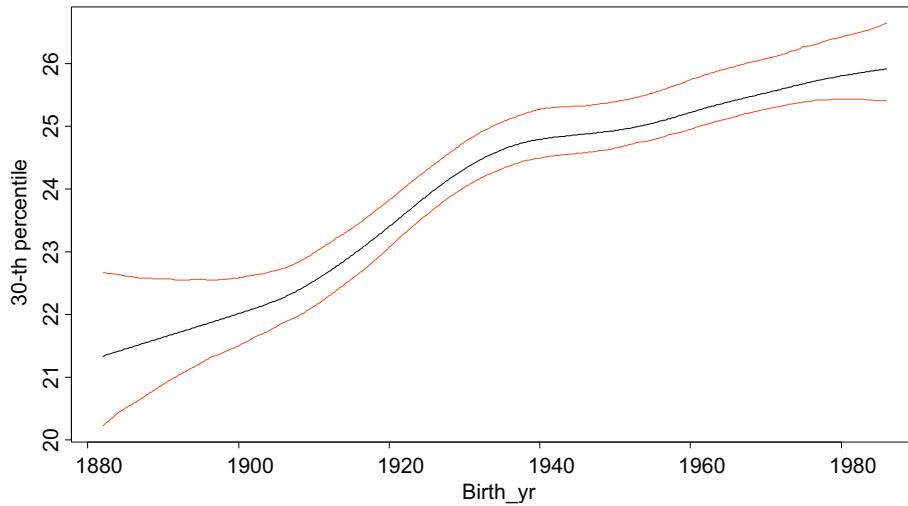
Fig. 16. 95% confidence intervals for BMI values of white men in the 30th percentile estimated by a bootstrap procedure.
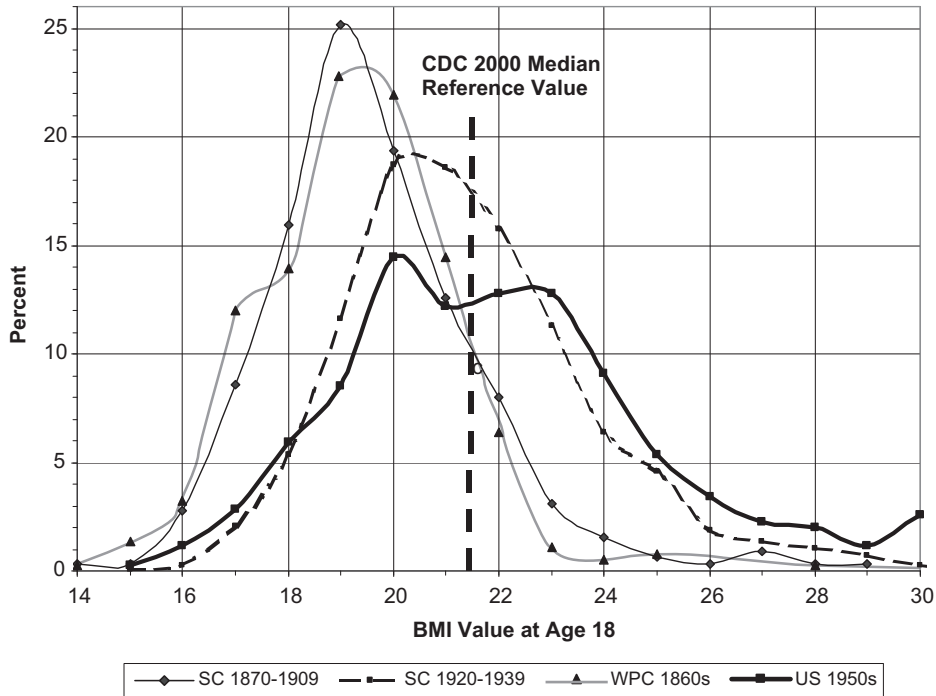

Fig. 17. Distributions of BMI values of white US 18-year-olds, 1860s–1950s. *Note*: SC = Cadets at The Citadel Military Academy in Charleston, SC; WPC = Cadets at the West Point Military Academy.

In many respects the rate of change of white female BMI deciles has a similar pattern to that of white men (Fig. 13). It remained fairly constant at the end of the 19th century and it also accelerated around the two world wars. However, the World War I acceleration lasted longer: the peak rate in the top deciles was reached in the mid-1930s instead of the mid-1920s as among white men. Moreover, the deceleration of the Great Depression was shallower and also lasted longer, until the very end of the

war. The subsequent acceleration also began at midcentury, as among white men, and lasted until about 1970 at which time the rate of change either remained constant or declined somewhat, particularly in the lower deciles. In short, the salient pattern of the rate of change of the decile curves is similar among white men and women. They both indicate that there were two periods of acceleration in BMI values following the two world wars. The main difference is in the lengths and turning points of the cycles.
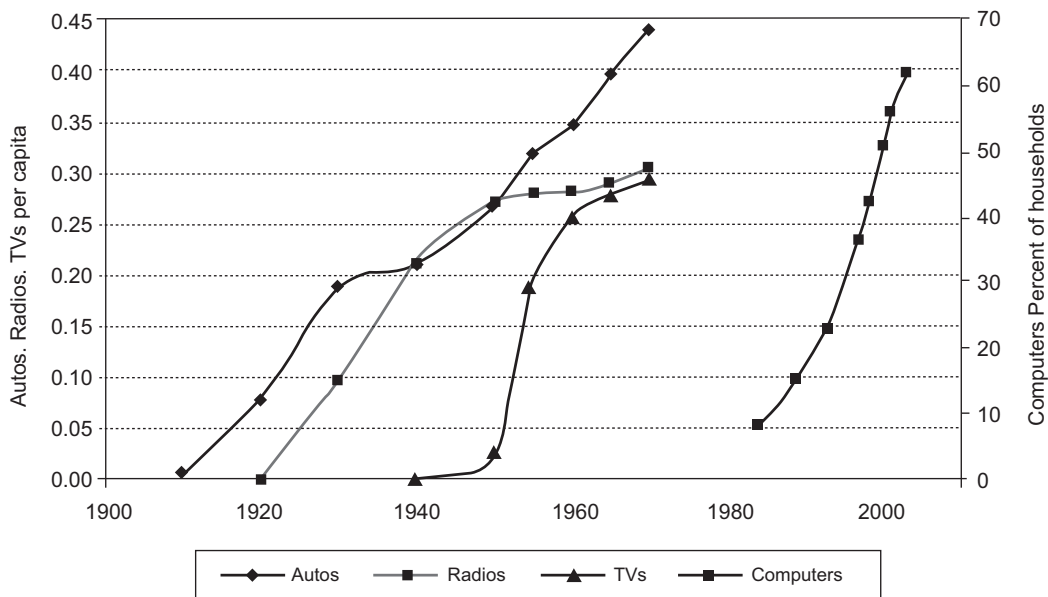
Fig. 18. The spread of major technologies in the 20th century in the USA.

In contrast, among blacks the pattern is quite different in the pre-World War II era but becomes similar to that of whites thereafter. Among black men (Fig. 14), the rate of change began at a higher level but declined practically continuously until World War II. The interdecile range was as large as among the white women to begin with, but did not increase at all until after World War II. In other words, the BMI distribution shifted to the right without becoming more skewed. Furthermore, in contrast to that experienced by whites, the World War I upswing was inconsequential and meant only a short interruption of the persistent decline in the rate of change. Moreover, the post-World War II upswing began earlier than among whites, i.e., in the early 1940s, and lasted until the mid-1960s, when a decline set in, somewhat earlier than that among white women.

The pattern among black women (Fig. 15) was similarly unique in the first half of the century insofar as the rate of change was already high to begin with and continued almost uninterrupted at that high level until midcentury. The range between the lowest and highest decile was large at the beginning and, as among black men, did not widen at all in the first half of the century, contrary to the pattern among the whites. Hence the BMI distribution did not become as skewed as among whites. The post-World War II upswing started around 1960 among the highest decile women, but was a bit delayed among the lowest deciles. The peak rate of change was reached around 1970 among the highest decile black and white women and in 1960 among black men. The highest decile white men did not have a local maximum during the post-World War II era as rates continued to rise until the end of the period.

6. Confidence intervals

The 95% confidence intervals were obtained for a given percentile curve as envelope bands, based on 500 boot-

straps from a simplified model, without weighing.[21] The diminishing number of observations before circa 1910 and after 1965 implies that the accuracy of the estimates diminishes in those periods.[22] The confidence intervals are often asymmetric (Fig. 16) – but the degree of asymmetry varies across the different deciles. This reflects the amount of information contained in the data for the estimation of a given decile. When we are estimating a central decile (i.e., close to the 50th), the restrictions provided by the data are close to being symmetric, and hence the CI is more symmetric as well (unless there is strong asymmetry in the BMI distribution itself). More extreme deciles are restricted by the data much more asymmetrically and hence, for them, we can typically observe extremely asymmetric CIs.

7. Conclusion

The lack of longitudinal data renders the determination of the secular trend of BMI values ambiguous regardless of

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[21] CI's were estimated together over times and quantiles. To be precise, we bootstrapped the model (actually the simplified model without weighting but with the same covariate structure for μ, σ, ν, τ) 500 times. Each resample out of these 500 gives model parameters that allow for computation of all quantile curves for all times (and much more). Then we searched for 2.5 and 97.5th percentiles over the 500 bootstrap resamples time point by time point, for each percentile (10, 20, …, 90). This gives a sort of "envelope" band that has the property that it covers 95% percentile curves over the bootstraps, for a given percentile.

[22] The precision of the estimates for years that have smaller sample sizes is obviously smaller. However, it decreases a little bit more slowly than the number of observations, because the smoothing procedure implies "borrowing information from neigbors". This is reflected in width of the 95% bootstrap confidence intervals (Fig. 16). They become wider close to the ends of the period under consideration, especially at the beginning.

the mode of analysis. The common wisdom, based on period effects, is that obesity as a public health problem emerged suddenly in the 1980s. However, the disadvantage of cross-sectional surveys, upon which all analysis has been based, is that the subject's current weight does not reveal when that weight was actually reached. That weight could have been reached at any time before measurement and maintained thereafter. Thus, period effects arguably provide an upper bound of the time when the current status was reached, whereas birth-cohort effects provide a lower bound insofar as the weight status at the time of the survey could have been reached already in childhood. Just when the weight gains actually occurred during the life cycle, however, remains uncertain. So far, research has concentrated on the (upper bound) period effects and our aim has been to fill the lacunae in the literature by estimating the (lower bound) birth cohort trends of the BMI deciles between 1882 and 1986 stratified into four ethnic and gender groups (net of age effects).[23]

While locating the beginning of the process is immaterial from some policy perspectives, in order to explore the associations with major technological discoveries of the 20th century (such as the radio, automobile, television, fast food) it is useful to obtain accurate estimates of not only the upper bound but also the lower bound of the timing of the evolution of BMI values. However, our findings have immediate policy implications as far as the weight reference charts, used in clinical practice are concerned. The fact that the acceleration in the prevalence of obesity likely started earlier than hitherto thought also implies that the current weight and BMI standards published by the Centers for Disease Control and Prevention are inaccurate. Reference charts are supposed to reflect what is "normal" within the society. In this case, however, they do not do so insofar as they incorporate values obtained between 1959 and 1992; they suggest that the values obtained in the midst of the obesity pandemic are actually normal. As a consequence, many overweight and obese children and youth are misled into believing that they do not fall into that category and remain erroneously complacent about their weight.

We focus in this study on estimating birth-cohort effects to fill a lacuna in the literature. Our study is motivated by the assumption that this additional perspective can contribute to our understanding of the development of the trend toward an increasing prevalence of obesity and have policy implications as well, for example, with regard to the weight standards used in clinical practice.

Admittedly, a limitation of our study is that we do not control for period effects. However, all studies that calculate trends using measurement years, i.e., period effects, have similar limitations: they failed to control for birth-cohort effects. Analyzing the data by birth cohorts, we find that the BMI values were increasing already by the beginning of the 20th century. While the early increases in BMI values probably brought about an improvement in biological well-being for the underweight portion of the population, soon too many BMI values reached and passed the danger zone.

It is also important to consider the shape of the BMI distribution and its evolution, not only the central tendencies, because various segments of the population might well be experiencing the weight gains in different ways. It is useful to know if the increase in BMI values has been proportional or not and if there were some segments of the population that bore a larger brunt of the burden or if there were segments which were totally isolated from the developments found in the central tendencies. We find, indeed, that the increase in the prevalence of obesity has been born disproportionately as the BMI distribution did not shift out uniformly but was distorted considerably over time. Hence, the deciles shifted outward unevenly like the veins of a fan, implying that over time the distribution became increasingly skewed to the right. In other words, the lower part of the distribution hardly increased in weight at all but the upper part increased more and more rapidly over time.

Even among African American women, who were the most susceptible to gains in weight, the lowest decile increased by only 2 BMI units during the whole century under consideration. However, the highest deciles shifted out by as much as 18–22 BMI units in all four groups. Translated into weight, these increases in BMI values imply that, for instance, in the first decile (10th percentile) a 64 in. (162.6 cm) tall women would have increased in weight by just 12 pounds (5 kg) whereas in the 90th percentile her weight would have increased by an amazing 128 pounds (58 kg) or by some 70%. After World War II the low – decile BMI values were actually stagnant or practically so and the only BMI values that increased rapidly were in the upper deciles. Consequently, the spread between the lowest and highest deciles almost tripled: in three of the groups the gap rose from approximately 8–25 BMI units while among black women the spread increased from 10 to 30 BMI units in the course of the century (Figs. 1–4).[24]

In addition to finding this extreme skewing of the BMI distribution, we also find that the rate of change of BMI values was far from uniform over the century. Rather, there was considerable variation over time in the rate at which the BMI decile curves increased (Figs. 6–9). The rate of change differed markedly among blacks and whites in the first half of the century. Among whites, both men and women, BMI values accelerated among those born after each of the two world wars and decelerated among cohorts of the Great Depression. In contrast, among black men the rate of change slowed during the first half of the century and then accelerated after World War II, while among black women it remained constant at a high level until World War II when it accelerated as in the other three

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[23] Although we control for income and education in the results reported above, we also did the analysis without these variables and found only minor changes in the results. We do not report these results for lack of space.

[24] Hence, among black women the difference in weight between the 10th and the 90th decile increased from 58 pounds (26 kg) to 174 pounds (79 kg).

groups. In other words, after the Second World War the rate of change in BMI deciles of blacks came to resemble that of whites with a postwar acceleration followed by a substantial deceleration around the late 1960s.

Their limitations notwithstanding, the historical data corroborate these findings in several important ways: (1) they indicate that mean BMI values were lower by c. 3 units at the beginning of the 20th century compared to the first values obtained in the national survey c. 1960, implying that of the 6 BMI unit increase in the mean values during the course of the century, about half was obtained among those born in the first half. This is a similar order of magnitude obtained in Fig. 6. (2) The BMI values of the convicts born at the end of the 19th century (Figs. 4 and 5) are almost identical to the BMI values of the men in the 50th decile of the national survey (Figs. 6 and 8) implying that the historical data are reasonably accurate in spite of the fact that they are not based on nationally representative samples. (3) The data on Citadel students (Fig. 2) indicate a very rapid increase in BMI values among those born after the First World War, which roughly corresponds to the acceleration in the rate of change we documented on the basis of the national data (Fig. 12). (4) The Citadel students were measured in the 1940s, that is to say, well before the beginning of the increase in BMI values according to the conventional view; hence the acceleration in their BMI values cannot be attributed to the conventional birth-cohort effect, that is to say, to our birth-cohort methodology. (5) It is also crucial that the BMI distribution of the Citadel students already showed substantial increase in skewness in the 1920s and 1930s, thereby resembling the uneven shift in the distribution of the national sample (Fig. 17). In other words, the fact that two quite different sources estimated with quite different methodologies corroborate each other in so many ways increases considerably our confidence that our birth-cohort approach provides a reliable perspective on trends.[25]

Thus, we feel safe to conclude that the transition to a post-industrial lifestyle affected an increasing portion of the US population's BMI distribution. Only the bottom two deciles managed to stay below overweight status among white men and women and black men, while among black women only the lowest decile escaped the grips of the creeping epidemic. This also implies that the revolutionary lifestyle changes of the 20th century affected the four groups under study somewhat differently. The reasons for these differences are outside the scope of the current study but would be well worth pursuing in the future in order to illuminate possible policy options.

Identifying the deep causes of the long-run trends is also outside of the scope of this study, but we do mention in passing that the persistent nature of the trend does suggest that its roots are embedded very deeply in the

social fabric and are nourished by a network of disparate and slowly changing sources as the 20th-century US population responded to a vast array of irresistible and impersonal socio economic and technological forces. The most obviously persistent among these were the major labor-saving technological changes of the 20th century, chiefly the industrial processing of food and with it the spread of fast-food eateries[26] and the associated culture of consumption, the rise of an automobile-based way of life, the introduction of radio and television broadcasting,[27] the increasing participation of women in the workforce, and the IT revolution, which, taken together, virtually defined American society in the 20th-century (Anderson et al., 2003; Bleich et al., 2008; Cutler et al., 2003; Lakdawalla et al., 2005; Lakdawalla and Philipson, 2009; Philipson and Posner, 2003, 2008; Popkin, 2004). Noteworthy in this regard is that the timing of the first accelerating phase among whites coincided with the spread of radios and automobiles, while the timing of the second accelerating phase of the 1950s, among both blacks and whites, coincided with the spread of television viewing and fast food outlets. In other words, the two upswings in the rate of change in the BMI decile curves following the two world wars were accompanied by the introduction of major technologies that favored a sedentary lifestyle (Fig. 18).[28] The decade of the 1950s is noteworthy also because a similar pattern was found among US children and adolescents whose BMI values accelerated similarly with the introduction and rapid spread of television and of fast food culture (Chou et al., 2004, 2008; Komlos et al., 2009; Powell et al., 2007). In other words, the introduction of television had an immediate impact on the weight of the population. The decline in the rate of increase in BMI values during the Great Depression of the 1930s and World War II reflects the decline in income which slowed the adoption of the labor-saving technologies and must have induced people to eat away from home less frequently.

Moreover, an increase in income inequality and a loosening of the economic safety net after c. 1980 put additional stress on the population that was conducive to weight gain (Offer et al., 2010). Government policy favored corporations over the public interest, implying that consumer protection was limited (Ruskin and Schor, 2005). The food industry spent trillions to induce people to consume and there was insufficient countervailing power to offset this psychological campaign. Combined with increasing affluence, a sedentary lifestyle, changes in dietary habits that included eating outside of the home more often and eating unhealthy energy-dense foods,

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[25] This is all the more so as the height of the students at The Citadel pertain to the time at which they entered the institution, that is in their late teens so that age effects play no role in the analysis. Moreover, the data end in the late 1940s so that period effects could not play a major role in the increase in BMI values.

[26] To illustrate the spread of fast-food culture, consider that White Castle, the first drive-in restaurant, was founded in 1921. McDonald's started operation in the late 1940s, Kentucky Fried Chicken in 1952, Burger King in 1954, Waffle House in 1955, Pizza Hut in 1958, International House of Pancakes in 1958, Taco Bell in 1962, and Subway in 1962.

[27] Television viewing has an additional effect because food and drink commercials increase food and drink consumption, and therefore obesity rates (Chou et al., 2008; Powell et al., 2007).

[28] Computers, on the other hand, did not have a similar impact. It seems that computer time might well have been a substitute for TV time.

multitasking that meant eating ready-made foods while watching television and not paying attention to the food being eaten were all developments that reinforced one another and led to the cultural transformation associated with the postindustrial nutritional revolution (Cutler et al., 2003; Hamermesh, 2010; Philipson and Posner, 2003, 2008; Lin et al., 2001; Popkin, 2004). For example, the share of total food expenditures spent on eating outside of the home increased from 24% in 1950 to 45% in 1995 (Offer, 2001, 2006, pp. 147, 149; Guthrie et al., 2002).[29]

In sum, our birth-cohort approach indicates that the transition to post-industrial BMI values certainly did not appear suddenly in the 1980s as the official view would have it. Rather, it most likely started in earnest among those born after World War I, and the BMI values continued to increase persistently punctuated by upsurges when the rate of change easily doubled, as after the two world wars. Moreover, African American women outpaced the other three groups being considered from the very beginning. Insofar as BMI values have been increasing over a century, researchers attempting to understand the causes of the current ominous developments need to redirect their focus from the final decades of the 20th century to much-longer-run processes of social, techno-logical, economic, and cultural change.

Acknowledgment

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[29] "The per-capita number of fast-food restaurants doubled between 1972 and 1997" (Chou et al., 2004, p. 568), and the calories available for consumption increased by some 20% in the late 1980s and 1990s. In turn, the consumption of high-calorie foods was associated with the increase in the number of hours worked by mothers (Anderson et al., 2003).

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