NBER WORKING PAPER SERIES

THE TREND OF MEAN BMI VALUES OF US ADULTS, BIRTH COHORTS 1882-1986 INDICATES THAT THE OBESITY EPIDEMIC BEGAN EARLIER THAN HITHERTO THOUGHT

John Komlos
Marek Brabec

Working Paper 15862
http://www.nber.org/papers/w15862

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 2010

The work was partly supported by the Institutional Research Plan of the Czech Republic AV0Z10300504 'Computer Science for the Information Society: Models, Algorithms, Applications'. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Trend of Mean BMI Values of US Adults, Birth Cohorts 1882-1986 Indicates that the Obesity Epidemic Began Earlier than Hitherto Thought
John Komlos and Marek Brabec
NBER Working Paper No. 15862
April 2010
JEL No. I00

ABSTRACT

The trend in the BMI values of the US population has not been estimated accurately because time series data are unavailable and because the focus has been on calculating period effects. In contrast to the prevailing strategies, we estimate the trend and rate of change of BMI values by birth cohorts stratified by gender and ethnicity born 1882-1986. We use loess additive regression models to estimate age and trend effects of BMI values of US-born black and white adults measured between 1959 and 2006. We use all the NHES and NHANES survey data and find that the increase in BMI was already underway among the birth cohorts of the early 20th century. The rate of increase was fastest among black females; for the three other groups under consideration, the rates of increase were similar. The generally persistent upward trend was punctuated by upsurges, particularly after each of the two World Wars. That the estimated rate of change of BMI values increased by 71% among black females between the birth cohorts 1955 and those of 1965 is indicative of the rapid increases in their weight. We infer that transition to post-industrial weights was a gradual process and began considerably earlier than hitherto supposed.

John Komlos
Department of Economics
Ludwig-Maximilians University
Ludwigstrasse 33/IV
Munich D-80539
GERMANY
and NBER
john.komlos@gmx.de

Marek Brabec
Pod Vodarenskou vezi 2
182 07, Praha 8
Czech Republic
mbrabec@szu.cz

Introduction

While descriptive statistics pertaining to the increasing prevalence of obesity among the US population have been extensively reported (Ogden et al., 2004, 2008; Flegal et al., 1998), the long-run trend in BMI values has yet to be identified convincingly. The extant studies tend to imply that the epidemic appeared suddenly, but tend to be imprecise on its beginnings. Troiano and Flegal (1998) reflect the mainstream view well in 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 studies, Ogden et al. (2006) point out that, "between 1980 and 2002, obesity prevalence doubled in adults aged 20 years or older."[2] In short, the emphasis has been on the 1980s as a pivotal point in the history of the obesity epidemic.

To be sure, there are some indications that the roots of the obesity pandemic do reach further back in time than the 1980s (Carson, 2009, Cuff, 1993; Coclanis and Komlos, 1995; Komlos, 1987). Flegal et al. (2002, p. 1724) suggest 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 epidemic must have begun earlier than the common wisdom supposes: "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, Carson 2009)." Nonetheless, in our view such snapshots hardly permit an unambiguous depiction of trends.[3]

However, note that all these studies refer to period effects (measurement years) and overlook birth-cohort effects. Insofar as it is not at all clear from the cross-sectional evidence when the measured weight status was reached, the focus on period effects does not lead to convincing trend estimates. Weight gains could have accumulated at anytime between birth and measurement. To be sure, current BMI values reflect current nutritional status, but the current level may have been reached prior to measurement and then retained unchanged. In fact, it could have been acquired at an early age (in terms of z-score), putting the individual on a trajectory that led to her current status.

In contrast to the consensus in the literature, we estimate trends by birth cohorts, because BMI at the time of measurement reflects the cumulative weight gains during the life course. After all, birth cohorts experienced similar social, economic, and technological changes; this cannot be said of measurement cohorts. For example, those measured in 1960 have been exposed to television viewing for different lengths of time during their lives. In contrast, all those born in 1960 have had access to TV viewing all their lives, regardless of when they were measured. Another reason to consider birth cohorts is that life-style habits and weight status acquired early in childhood tend to persist into adulthood (Freedman et al., 2005).

Actually, one can consider period effects as the upper bound for the time when the weight gains occurred, whereas birth-cohort effects provide the lower bound. Thus, neither approach can be considered to be superior to the other. In the absence of longitudinal data, that is to say, with cross sectional data sets such as the ones we are about to analyse, both approaches have a legitimate place in scientific inquiry, even if neither approach is fully specified because of collinearity (period – age = cohort). However, a considerable technical advantage of the birth-cohort approach is that instead of having only 5 data points from the cross-sectional surveys (1959-2006), from which merely 4 differences can be calculated, we obtain data continuously for the 104 years from 1882-1986.[4] Furthermore, the birth-cohort approach also enables us to calculate the annual rate of change of BMI values, whereas the period-effect approach does not.

However, several studies broke new ground recently in the analysis of obesity trends. Burkhauser, Cawley, and Schmeiser (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, go further, concluding 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 beginning at least …in the 1950s, but possibly earlier." This conclusion is in line with the fact that many of the technological and life-style innovations that are frequently associated with an obesogenic environment -- fast-food restaurants, automobiles, TV, radio, and labor-saving household devices -- predated the 1980s, in some cases by many decades.

In addition to the period trends reported up to now, and the cohort trends about to be estimated, a third approach to the analyses is the age-period-cohort models (Hobcraft, Menken, Preston 1982; Holford, 1992). This class of models attempt to solve the problem of collinearity (as age, period, and cohort are linearly related: period – age = birth cohort). Reither et al. (2009) use such a model on data from the National Health Interview Surveys. They "demonstrate that both secular change and birth cohort membership have independently contributed to elevated odds of obesity." Their study differs from ours in several ways: a) they analyze obesity while we analyze mean BMI values; b) in order to decompose the trend into a period and cohort effects in spite of the identification problem and the concomitant collinearity they need to make several crucial assumptions, the plausibility of which is difficult to ascertain independently. It is not clear the extent to which their results are sensitive to these assumptions; c) they use a sample that relies on self-reported weight and height, while we use measured values. Although they adjust for the inaccuracies associated with such data by increasing BMI values by about 1 unit, the possibility that errors remain cannot be ruled out. This is particularly the case, because the extent of mis-reporting varies by education, and because their dependent variable is dichotomous, namely individuals with BMI>30. Consequently, errors in the individual BMI values can lead to mis-classification of individuals into the obese/non-obese category. Another example of such models is provided by Sassi et al. (2009). They also use the same data set as Reither et al. (2009) and arrive at similar conclusions, without, however, controlling for race or correcting for the fact that the data are self-reported.

We do not use an APC (Age, Period, Cohort) model because we have little faith in their validity. It is not clear which one we should choose (frequentist or Bayesian), and with no guarantee that their results would be consistent. The Bayesian approach tries to solve the indeterminacy in the data by imposing prior assumptions on the model which appears somewhat arbitrary (the validity of the conditions remains an open question). We prefer the simpler approach we employ here – cohort effects share an attribute with period effects in that they provide an accurate bound estimate of the trend in BMI values (lower and upper bounds respectively). Thus, our main goal is to fill a lacunae in the literature by estimating the lower bound trend, i.e., trends of the BMI values by birth cohorts of US adults stratified by gender and ethnicity in greater detail and somewhat more convincingly than has been done up to now. A considerable advantage of this approach is that it enables us to calculate the rate of change of the trend.

Data and Method

We estimate for the first time 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.[5] We recalculate the survey weights provided in the data sets according to the formula given in Korn and Graubard (1999)[6] and use these weights throughout the analysis. We limit the analysis to US-born adults - those above the age of 19 - (white male, white female, black male, and black female are fitted separately). In order to ensure comparability over time and to reduce uncontrolled heterogeneity[7] (Rosenbaum 2005) (through immigration, for example) we confine our analysis to non-Hispanic blacks and non-Hispanic whites. (Henceforth, we drop the designation non-Hispanic for the sake of brevity.) (N =4976 Black Women, 14,083 white women, 4,135 black men, and 12,651 white men).[8]

We estimate the following additive semi-parametric loess models, which enable us to estimate the shape of the trend flexibly by the data, rather than determining it ex ante:[9]

$$(1)\quad BMI_{ik} = \mu_k + lo_k(Age_{ik}) + lo_k(Birth\_yr_{ik}) + lo_k(PIR_{ik}) + \sum_{m=1}^{3} \alpha_m (E_{imk}) + \varepsilon_{ik}$$

where: BMI_{ik} is the BMI value for the *i*-th individual of *k*-th stratum (*k*=1, 2, 3, 4 corresponding to white males, white females, black males, and black females). $lo_k(.)$ is the smooth nonparametric term (Wood, 2006). It is estimated by (locally linear) loess, for each stratum separately via backfitting algorithm (as is usual in the context of GAM, or generalized additive models, Hastie and Tibshirani, 1990; Wood, 2006). Actual fitting was done in R.[10] PIR is the poverty-income ratio[11] (Fisher, 1992). E_{imk} is the level of education in three categories: without a high-school degree, with a high-school degree, and with some college education. ε_{ik} is a random term with zero mean and variance given by survey weights (as their reciprocals).[12]

Admittedly, there is a limitation to estimating trends by birth cohorts, insofar as ages are not evenly distributed during the period considered. At the beginning of the period we have only older ages in the sample, while toward the end we have mainly younger adults. In other words, cohort and age effects are correlated, making attempts to attribute changes to one or the other variables fragile. This sample composition implies that we should consider the estimates particularly at the ends as preliminary, and subject to revision as more data become available. Furthermore, this hurdle prevents us from testing for interaction effects. Nonetheless, we have chosen to include these observations at the beginning and end of the period under consideration insofar as they do enable us to provide some conjectures regarding past and future developments. Our reference to dates pertain to dates of birth rather than to dates of measurement.

Results

We estimated model (1) after selecting it among several possibilities based on crossvalidation optimization (with respect to the span parameter) and checked its performance using residual analysis and 1000 bootstrap resamples (each having the same number of observations as the original data set).[13] We report the estimated functions of eq. (1) graphically (calibrating the levels for a person of age 50 with a high-school degree and PIR value of 2). For some of the estimated functions we also report their annual rate of change.[14]

The trend of increasing BMI values, which began among those born in the late-19th and early-20th centuries, has been most rapid among black females (Figure 1) throughout the century. We calculate the derivative of the BMI function in Figure 1 to obtain Figure 2. The results indicate a quite synchronous acceleration after World War I among three of the four groups considered. Black females are the exception whose BMI values was already increasing more rapidly than that of the other three groups even at the beginning of the period considered. The upswing among black females, which began somewhat later (in the late 1920s), was smaller and shorter, but their rate of change remained above that of the other three groups throughout the century. Moreover, the rapid increase in the rate of change tended to be temporary and was reversed during the Great Depression and World War II. However, the reversal was also delayed among black women. During the war the rate of change was only slightly above zero among men, both black and white. However, among women, both white and black, the rate of change remained at about 0.1 and 0.14 points per annum, even during the war. A decade after the end of the war, black BMI values begun to accelerate extremely rapidly. Among black females the rate of change of BMI values increased from circa 0.14 points per annum in 1955 to circa 0.24 points by 1965 (a 71%

jump), while among black men it almost quadrupled, from about 0.04 points per annum c. 1950 to 0.15 in 1965. However, by c. 1965-1970 the rate of change leveled off in all groups although among black females the level was at an extremely high level of 0.25 points; in fact, the only further change in BMI values was a decline among black men (Figure 2).

Figures 1 and 2 about here

The age effects are quite substantial, and are largest among black females (Figure 3). The peak is reached near age 60-70 in all four groups; after that a decline is evident except among black males, whose BMI values stagnate after reaching a plateau.[15] The income (PIR) effects differ the most among the four groups (Figure 4). Black females in the low- and medium-income ranges are the heaviest group, but a rapid weight decline accompanies an increase in income. The BMI values of white males increases to about a PIR value of 3 or so and then declines somewhat. The BMI of black males differs from that of white males only in that, after having reached a PIR value of about 3, it does not decline. Among white females, the BMI value decreases from the very beginning of the income range, but not linearly. Lastly, the education effect is small and not as anticipated: BMI does not decline systematically with level of educational attainment (Figure 5). The possible reason is that these effects are net of income.

Figures 3 - 5 about here

Iso-BMI lines depict combinations of age and birth cohorts with a constant BMI value at increments of one unit (Figure 6). Their advantage is that they enable us to see simultaneously the effect of two of the independent variables on BMI, rather than only one of them as in the other figures. We note that both age and cohort effects are important even if the latter appear to be more influential. For instance, a 30-year-old black women born in 1920 had a BMI value of 21, whereas by about 1940 this would become the BMI value of a 20-year-old. A comparison of white and black women's contour maps indicates that the "hill of obesity" is much steeper among the latter as the closer are the lines the more rapidly do the BMI values rise. One also notes the substantial differences in the age effects. Thus, such two-dimensional contour maps do provide visual insights that are not easily gained by one dimensional ones.

Figures 6 and 7 about here

In an alternate specification (as a sensitivity analysis) we divide the white male sample into two groups, in order to estimate eq. (1) separately for those who were born before and those who were born after 1940. We report only the graph for the estimated time trend, which indicates that the degree of difference between the two models is not substantial (Figure 8). The estimate of the function is shifted up slightly after 1940. The only major difference appears in the period prior to 1900: the second model estimates constant BMI values for those two decades.

Figure 8 about here

Discussion

Our primary goal has been to estimate long-run trends in mean BMI values of US adults by birth cohorts between 1882 and 1986 stratified into four ethnic and gender groups (net of age effects).[16] This is the first analysis of BMI trends in which all the NHANES samples have been concatenated, thereby providing a long-range perspective by birth cohort. The NHANES BMI data are the most accurate insofar as they are based on measured values rather than self reported ones as in most other surveys.

The lack of longitudinal data renders the determination of the secular trend in BMI values rather difficult. The lack of clear idea of when the obesity epidemic began renders the analysis of its causes challenging. The disadvantage of cross-sectional data is that a person's weight at a point in time, does not reveal when that weight was reached. Insofar as current BMI is a cumulative measure of weight gains from birth to date of measurement, period effects arguably provide an upper bound for the time when the current weight was reached, whereas birth-cohort effects provide a lower bound insofar as the weight status could have been reached at any time between birth and measurement. 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. Our aim has been to fill the lacunae in the literature by estimating the (lower bound) birth cohort trends.

Our birth-cohort approach indicates that the transition to a post-industrial BMI values occurred gradually throughout the 20th century and possibly started much earlier than hitherto supposed, with black women outpacing the other three groups from the very beginning (Figures 1 and 2). However, the rate of change in BMI values was anything but continuous. Rather, the general upward trend was punctuated by upsurges, particularly after each of the two World Wars. The birth cohorts of the 1920s experienced a rapid increase in BMI values. Notably, this generation was among the first to experience the introduction of radio broadcasting and the rapid spread of automobiles. During the Great Depression and World War II, however, the rate of increase decelerated and reached almost zero among men, both black and white. Indicative of the rapid increases after the war, in striking contrast, among black females the rate of change in BMI values increased by 71% between 1955 and 1965, while among black men it nearly quadrupled between ca. 1950 and 1965. However, by circa 1965-70 the rate of change reached a plateau, although among black women the plateau was at a very high level of 0.25. The only subsequent change was a decline in BMI values among black men (Figure 2).[17]

The limitation of the our study is that we do not control for period effects. However, similar limitations apply to all studies published hitherto which calculated trends using measurement years, i.e., period effects: they failed to control for birth cohort effects. To be sure, some researchers recently have become aware of this issue and explore birth cohort effects of the obesity epidemic using an alternative statistical strategy, by attempting to decompose age, period, and cohort (APC) effects. However, this approach is based on hard-to-verify assumptions. In this sense, the decomposition of (originally perfectly collinear) the three effects comes at a relatively large price. This well-known problem is particularly acute for the NHANES data sets under scrutiny on account of the fact that not all combinations of birth year and age are available. Therefore, we do not attempt to produce APC decomposition in which we do not place sufficient trust to begin with.

Sassi et al. (2009) and Reither et al. (2009) estimate such period-age-cohort models. In spite of the considerable differences in estimation techniques employed, as noted in the introduction, and in the different data set used, there are several similarities between their results and ours. Both studies also find that cohort effects were substantial although they infer that their significance declined during the first half of the 20th century. Reither et al. find that birth cohort effects of the probability of obesity increased after 1955, and that they were particularly rapid among black women, increasing by some 62% between the birth cohorts of 1955 and 1975. However, there were differences as well. They find that overall period effects were more important than cohort effects: they "are principally responsible for the obesity epidemic in the U.S. population."

Sassi et al. (2009) do not stratify their results by ethnicity or gender. Nonetheless, they are in agreement with the latter study in that they also argue that cohort effects of obesity were declining in the first half of the 20th century (p. 24) without providing a convincing explanation for this finding. They also find an upturn in the cohort effects but slightly later than Reither et al. (2009) do. Sassi et al. also analyse trends in overweight (Reither et al. do not) and find that the cohort effects have a similar trend to that of obesity with the difference that the upswing of the early 1960s is much attenuated. However, we do not learn how sensitive their results are to the various assumptions made.

Our study, its limitations notwithstanding, demonstrates in the least that the widespread belief that the American obesity pandemic appeared suddenly in the 1980s is based on weak evidential basis and on its surface rather implausible. Rather, our analysis indicates that the transition manifested itself gradually though persistently over an extended period of time, beginning among those born immediately after the First World War. Thus, the transition to a post-industrial lifestyle and the associated increases in BMI values may well have spanned the entire 20^{th} century. The rate of change in the BMI values was punctuated by upsurges among the 1920s birth cohort as well as among the generation born watching television.

Evidently the BMI values of all four (gender/ethnic) groups considered here accelerated in the 1920s as well as in the 1950s, at the time when calorie-saving technological changes were most obvious. Of course, changes in dietary habits including the anchoring of a fast-food culture in the social fabric reinforced and greatly acerbated the trend toward increasing weight. The decade of the 1950s is particularly noteworthy, for the acceleration in BMI values of US children and adolescents during this decade accompanied the introduction and rapid spread of television and of fast food culture[18] (Chou et al., 2004, 2008; Komlos et al., 2009, Powell et al., 2007).

Identifying the causes of this long-run trend are outside of the scope of this study, but we do note that the “creeping” nature of the epidemic, as well as its persistence, does suggest that its roots have been embedded deep in the social fabric and are nourished by a network of disparate sources, slowly changing as the 20th-century US population responded to a vast irresistible impersonal socio-economic and technological forces. The most obviously persistent among these were the major labor-saving technological changes of the 20^{th} century, chiefly the industrial processing of food and with it the spread of fast-food eateries and the associated culture of consumption, the rise of an automobile-based way of life, the introduction of radio and television broadcasting,[19] the increasing participation of women in the work force, and the IT revolution which taken together virtually defined American society in the 20th-century (Anderson, Butcher, and Levine, 2003; Bleich et al., 2008; Cutler, Glaeser, and Shapiro, 2003; Lakdawalla, Philipson, and Bhattacharya, 2005; Lakdawalla, Philipson, 2009; Philipson and Posner, 2008; Popkin, 2004). 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 less often away from home.

Moreover, psychological aspects of what has been called "the age of Milton Friedman" (Shleifer, 2009), featuring an increase in income inequality and a decrease in economic safety nets, put additional stress on the population that was conducive to weight gain (Ulijaszek and Offer, 2009). To make matters worse, government policy favored corporations over the public interest implying that consumer protection was limited (Ruskin and Schor, 2005). The food industry spent trillions to convince people to consume and there was insufficient countervailing power to offset this psychological program. Combined with increasing affluence, a sedentary lifestyle, changes in dietary habits that included eating more outside of the home and eating unhealthy foods such as snacks, multitasking that meant eating ready-made food while watching television, these developments reinforced one another and led to the cultural transformation associated with the post-industrial nutritional revolution (Cutler et al., 2003; Hamermesh, 2010, Philipson and Posner, 2003, 2008; Lin et al., 2001). 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).[20]

As the BMI values of the four ethnic/gender groups considered here are distinct from one another to some extent, so too the technological, dietary, and lifestyle changes enumerated above seem to have had distinctly different effects on each of the four groups. The reasons for these differences are outside of the scope of the current study as is the deep analysis of the causes of the trend. While the early increases in BMI probably brought about an improvement in biological well-being for a large portion of the population, the rapid increases after the Second World War soon raised too many BMI values into the danger zone.

Insofar as BMI values have been increasing gradually over a century, researchers attempting to understand the causes of the pandemic need to redirect their focus from the 1980s and thereafter to much longer run processes of social, technological, economic and cultural change. The finding also implies that policies to attenuate or reverse the trend will have to reach deep into the social fabric and take into consideration that such socio-economic forces generally change at glacial pace.

REFERENCES

Anderson PM, Butcher KF, Levine PB. 2003. Economic Perspectives on childhood obesity. *Econ Perspec* (Federal Reserve Bank of Chicago), 3:30-48.

Bleich S, Cutler D, Murray C, Adams A. 2008. Why is the Developed World Obese?. Annual Rev of Public Health 29:273-295.

Burkhauser RV, Cawley J, Schmeiser MD. 2009. The Timing of the Rise in U.S. Obesity Varies With Measure of Fatness. Economics and Human Biology 7:307-318.

Carson SA. 2009. Racial differences in body mass indices of men imprisoned in 19th century Texas. Economics and Human Biology 7: 121-127.

Chou SY, Grossman M, Saffer H. 2004. An economic analysis of adult obesity: results from the Behavioral Risk Factor Surveillance System. Journal of Health Economics 23:565-587.

Chou SY, Rashad I, Grossman M. 2008. Fast-Food Restaurant Advertising on Television and Its Influence on Childhood Obesity. Journal of Law and Economics 51:599-618.

Cleveland WS. 1979. Robust Locally Weighted Regression and Smoothing Scatterplots. *Journal of the American Statistical Association* 74:829-836.

Cleveland WS, Devlin SJ. 1988. Locally Weighted Regression: An Approach to Regression Analysis by Local Fitting. *Journal of the American Statistical Association* 83:596-610.

Coclanis P, Komlos J. 1995. Nutrition and Economic Development in Post-Reconstruction South Carolina: an Anthropometric Approach. Soc Sci Hist 19:91-116.

Cuff T. 1993. The Body Mass Index Values of Mid-Nineteenth-Century West Point Cadets: A Theoretical Application of Waaler's Curves to a Historical Population. Hist Meth 26:171-82.

Cutler DM, Glaeser EL, Shapiro JM. 2003. Why Have Americans Become More Obese?. *J of Econ Perspectives* 17:93-118.

Fisher, GM. 1992. The development and history of the poverty thresholds. Soc Sec Bull 55:3-14.

Flegal KM, Carroll M, Ogden C, Johnson C. 2002. Prevalence and Trends in Obesity Among US Adults, 1999-2000. J of the Am Med Ass 288: 1723-27.

Flegal, KM, Carroll M, Kuczmarski RJ, Johnson C. 1998. Overweight and obesity in the United States: prevalence and trends, 1960-1994. Int J of Obesity 22:39-47.

Freedman DS, Khan LK, Serdula MK, Dietz WH, Srinivasan SR, Berenson G. 2005. The relation of childhood BMI to adult adiposity: the Bogalusa Heart Study. Pediatrics 115:22–27.

Guthrie J, Lin Biing-Hwan, Brazao E. 2002. Role of Food Prepared Away from Home in the American Diet, 1977-78 versus 1994-96: Changes and Consequences. J. of Nutrition Education and Behavior 34:140-150.

Hamermesh D. 2010. Incentives, time use and BMI: The roles of eating, grazing and goods. Econ and Hum Biol 8:2-15.

Hastie T, Tibshirani RM. 1990. Generalized additive models. Chapman and Hall. London.

Helmchen LA, Henderson R. 2004. Changes in the distribution of body mass index of white US men, 1890–2000. Ann of Hum Biol 31:174–181.

Hobcraft J, Menken J, Preston S. 1982. Age, period, and cohort effects in demography: a review. Pop Index 48(1): 4-43.

Holford TR. 1992. Analysing the temporal effects of age, period and cohort. Stat Meth

Medical Research 1:317-37.

Komlos J. 1987. The Height and Weight of West Point Cadets: Dietary Change in Antebellum America. J of Econ Hist 47: 897-927.

Komlos J, Baur M. 2004. From the Tallest to (One of) the Fattest: The Enigmatic Fate of the Size of the American Population in the Twentieth Century. *Econ and Hum Biol* 2:57-74.

Komlos, J, Breitfelder A, Sunder M. 2009. The transition to post-industrial BMI values among US children. *Am J of Hum Biol* 21:151-160.

Korn EL, Graubard BI. 1999. *Analysis of Health Surveys*. New York: John Wiley and Sons.

Lakdawalla D, Philipson T, Bhattacharya J. 2005. Welfare-Enhancing Technological Change and the Growth of Obesity. Am Econ Rev 95:253–257.

Lakdawalla D, Philipson T. 2009. The growth of obesity and technological change. Econ and Hum Biol. 7: 283-293.

Lin Biing-Hwan, Guthrie J, Frazao E. 2001. American Children's Diets not Making the Grade. Food Review 24:8-17.

Norton K, Dollman J, Martin M, Harten N. 2006. Descriptive epidemiology of childhood overweight and obesity in Australia: 1901-2003. Int J of Pediatric Obesity 1:232-238.

Offer A. 2001. Body-Weight and Self-Control in the USA and Britain since the 1950s. Soc Hist of Medicine 14:79-106.

Offer A. 2001. The Challenge of Affluence: Self-control and Well-being in the USA and Britain since 1950. Oxford University Press.

Ogden CL, Carroll MD, McDowell MA, Flegal KM. 2007. Obesity among adults in the United States -- no change since 2003-2004. NCHS Data Brief no 1: 1-8.

Ogden CL, Carroll MD, Curtin LR, McDowell MA, Tabak CJ, Flegal KM. 2006. Prevalence of overweight and obesity in the United States, 1999-2004. J of the Am Med Ass 295:1549-1555.

Ogden CL, Carroll MD, Flegal KM. 2008. High Body Mass Index for Age Among US Children and Adolescents, 2003-2006. J of the Am Med Ass 299:2401-2405.

Ogden CL, Fryar CD, Carroll MD, Flegal M. 2004. Mean Body Weight, Height and Body Mass Index, United States 1960-2002. Advance Data from Vital and Health Statistics, No. 347, October 27, US Department of Health and Human Services, Centers for Disease Control for Health Statistics.

Philipson T, Posner, R. 2003. The Long Run Growth of Obesity as a Function of Technological Change. *Perspectives in Biology and Medicine* 46:87-108.

Philipson T, Posner, R. 2008. Is the Obesity Epidemic a Public Health Problem? A Decade of Research on the Economics of Obesity. NBER Working Paper 14010.

Popkin BM. 2004. The Nutrition Transition: Worldwide Obesity Dynamics and Their Determinants. *Int J of Obesity* 28:S2-S9.

Powell LM, Szczypka G, Chaloupka FJ, Braunschweig CL. 2007. Nutritional Content of Television Food Advertisements Seen by Children and Adolescents in the United States. Pediatrics 120:576-583.

Rashad I, Grossman M, Shin-Yi Chou. 2006. The Super Size of America: An Economic Estimation of Body Mass Index and Obesity in Adults. *Eastern Econ J* 32:133-148.

Reither EN, Hauser RM, Yang Y. 2009. Do Birth cohorts matter? Age-period-cohort analyses of the obesity epidemic in the United States. Soc Sci & Med 69:1439-1448.

Roelants M, Hauspie R, Hoppenbrouwers K. 2009. References for growth and pubertal development from birth to 21 years in Flanders, Belgium. Ann of Hum Biol 36:680-694.

Rosenbaum PR. 2005. Heterogeneity and Causality: Unit Heterogeneity and Design Sensitivity in Observational Studies. The Am Statistician 59: 147–152.

Sassi F, Devaux M, Cecchini M, Rusticelli E. 2009. The obesity epidemic: analysis of past and projected future trends in Selected OECD countries. OECD Health Working Papers No. 45.

Shleifer A. 2009.The Age of Milton Friedman. *J of Econ Literature* 47: 123–135.

Sunder M. 2004. The height of Tennessee convicts: another piece of the “antebellum puzzle. Econ and Hum Biol 2:75-86.

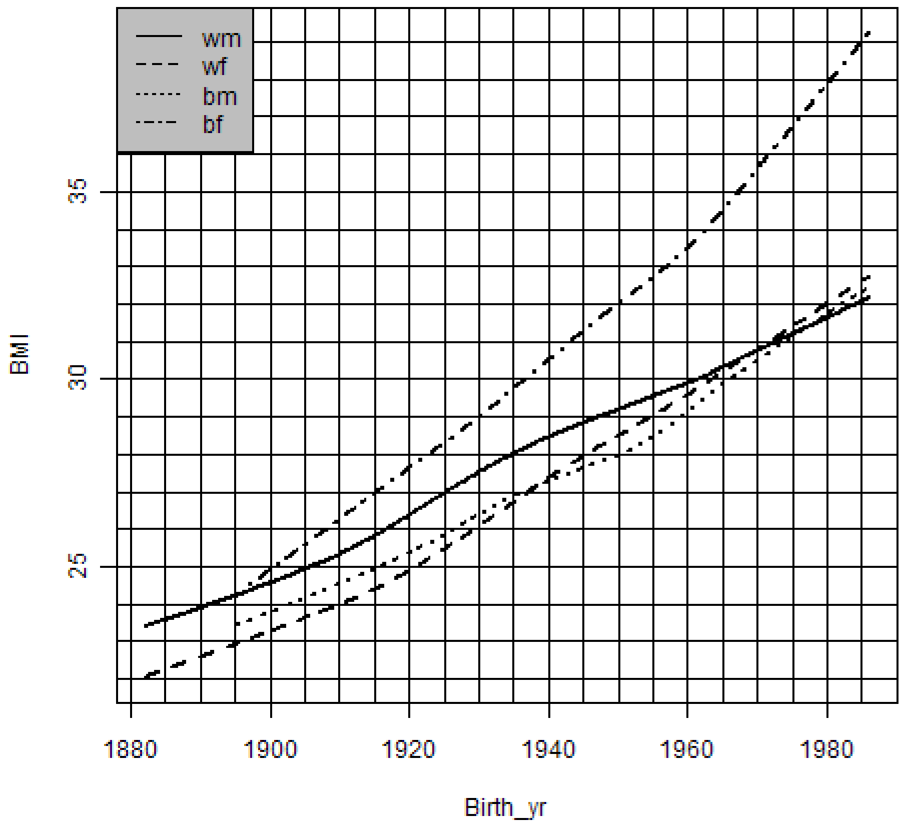
Troiano RP, Flegal KM. 1998. Overweight Children and Adolescents: Description, Epidemiology, and Demographics. Pediatrics 101:S497-504.

Offer A, Ulijaszek S. 2009. Obesity: the welfare regime hypothesis. Workshop 27/28 November 2009, University of Oxford.

Wood SN. 2006. Generalized additive models: an introduction with R. Chapman Hall, CRC Press.

Yatchew A. 1998. Nonparametric regression techniques in economics. J of Econ Lite 36:669-721.

Figure 1. Trend of BMI values by birth cohorts of US-born White and Black Adults



Note: Calibrated at PIR = 2 for those with a High School Diploma born in 1950.

Figure 2. Rate of Change of BMI Values by birth cohort in Figure 1.

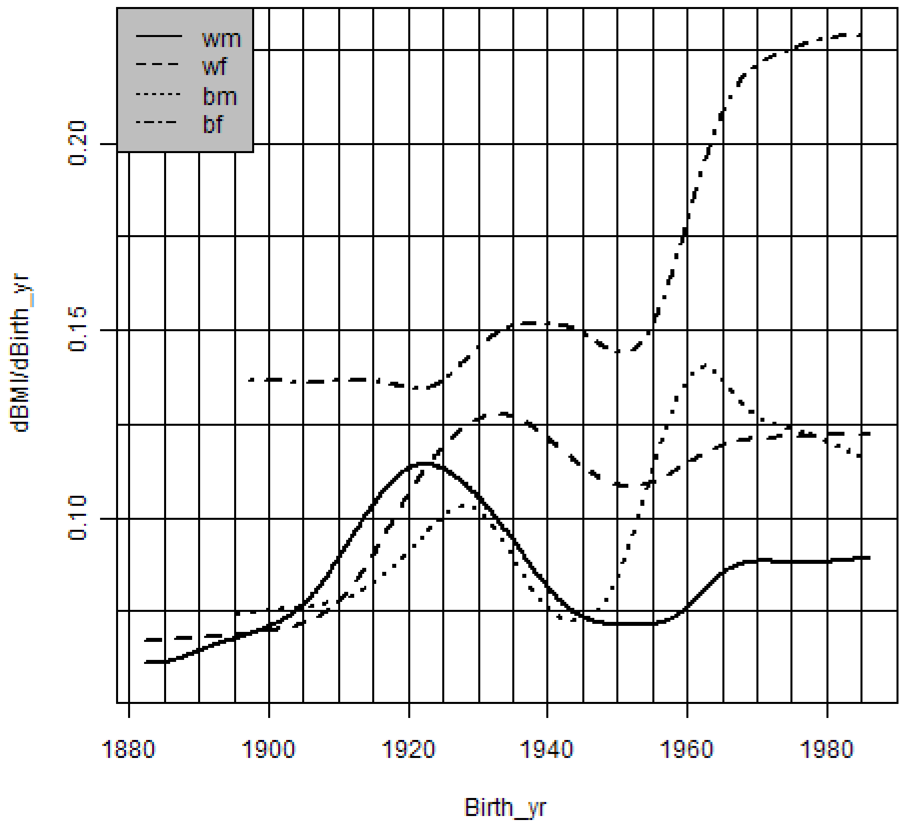
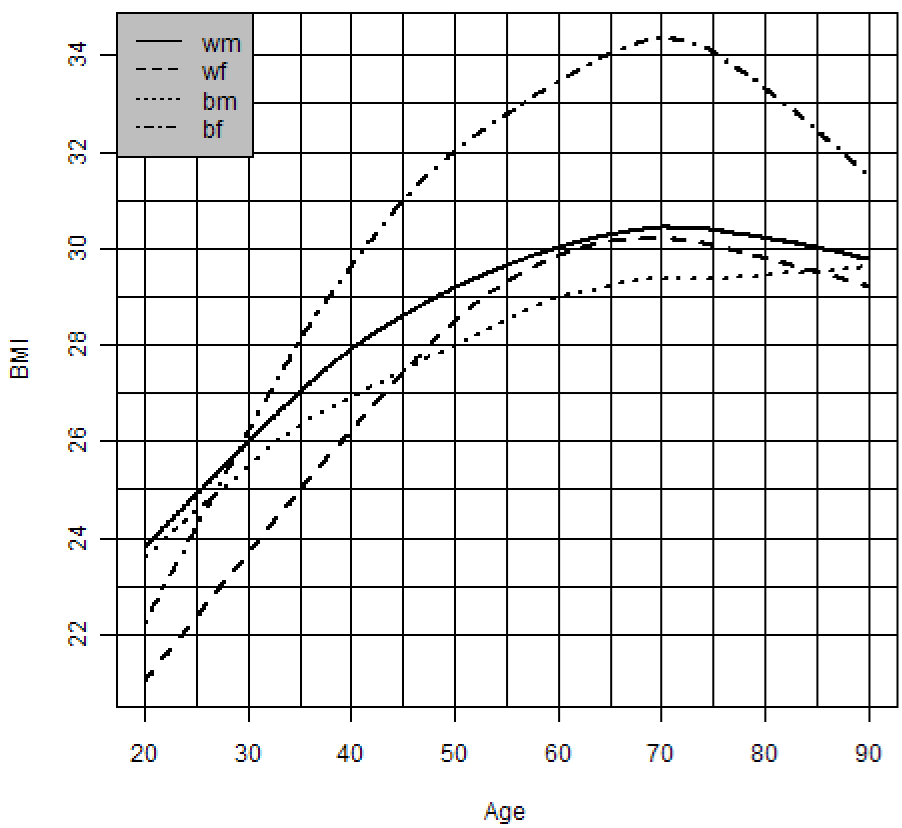


Figure 3. BMI Values by Age of US-born White and Black Adults



Note: Calibrated at PIR = 2 for those with a High School Diploma born in 1950.

Figure 4. BMI values by PIR of US-born White and Black Adults

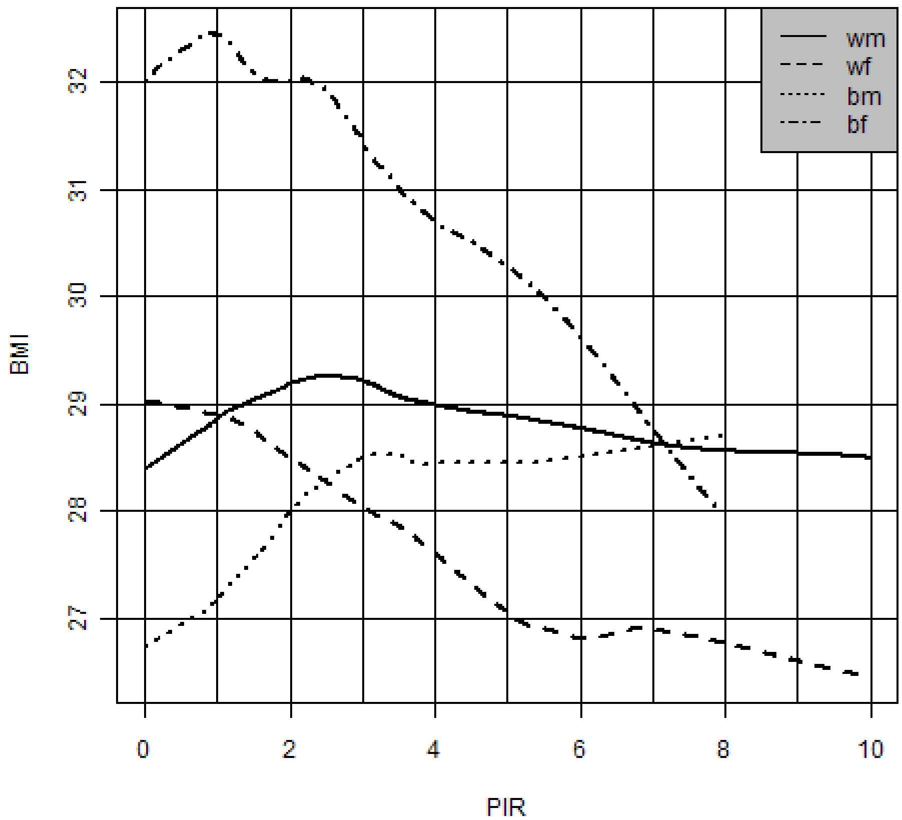


Figure 5. BMI values by level of Education of US-born White and Black Adults

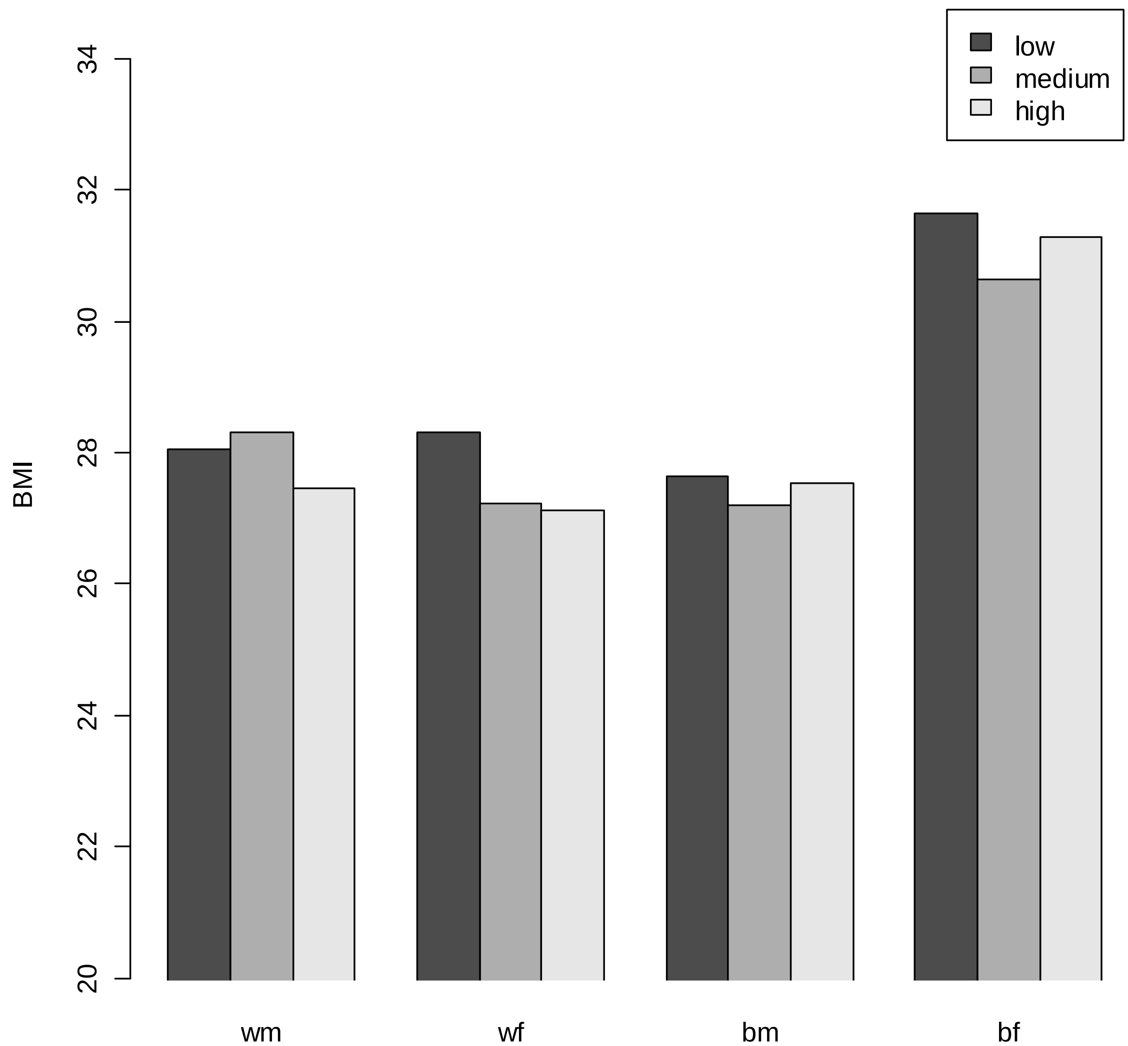


Figure 6. Iso-BMI lines for given age birth cohort combinations, White Females.

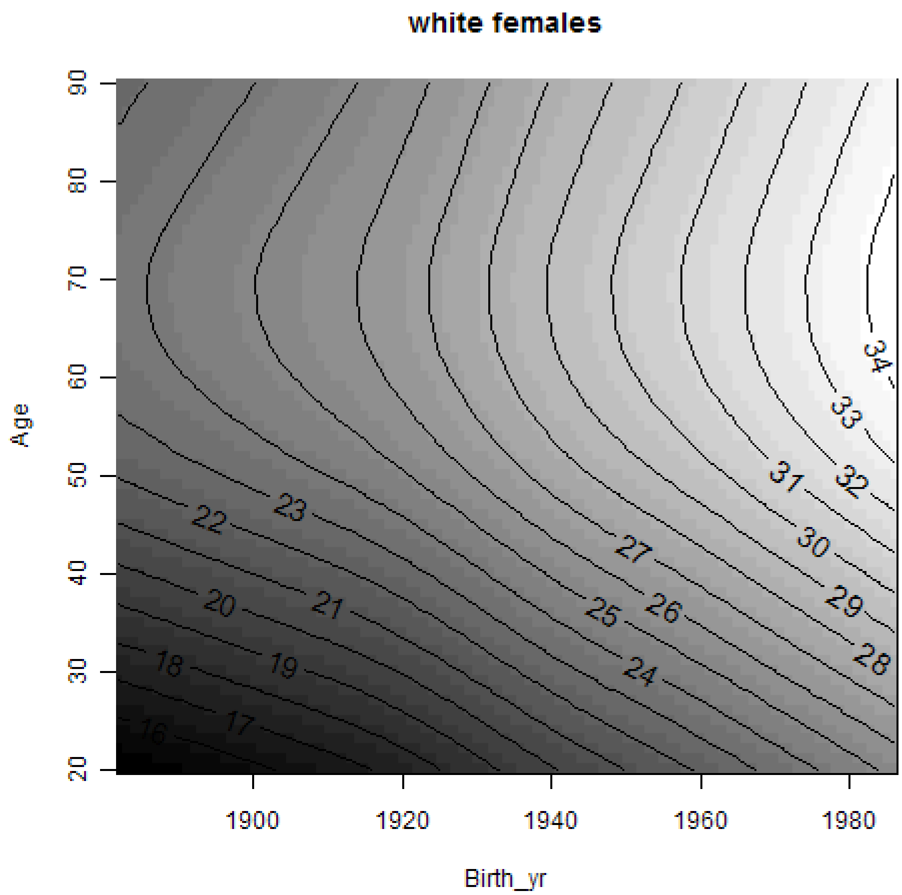


Figure 7. Iso-BMI lines for given age birth cohort combinations, Black Women

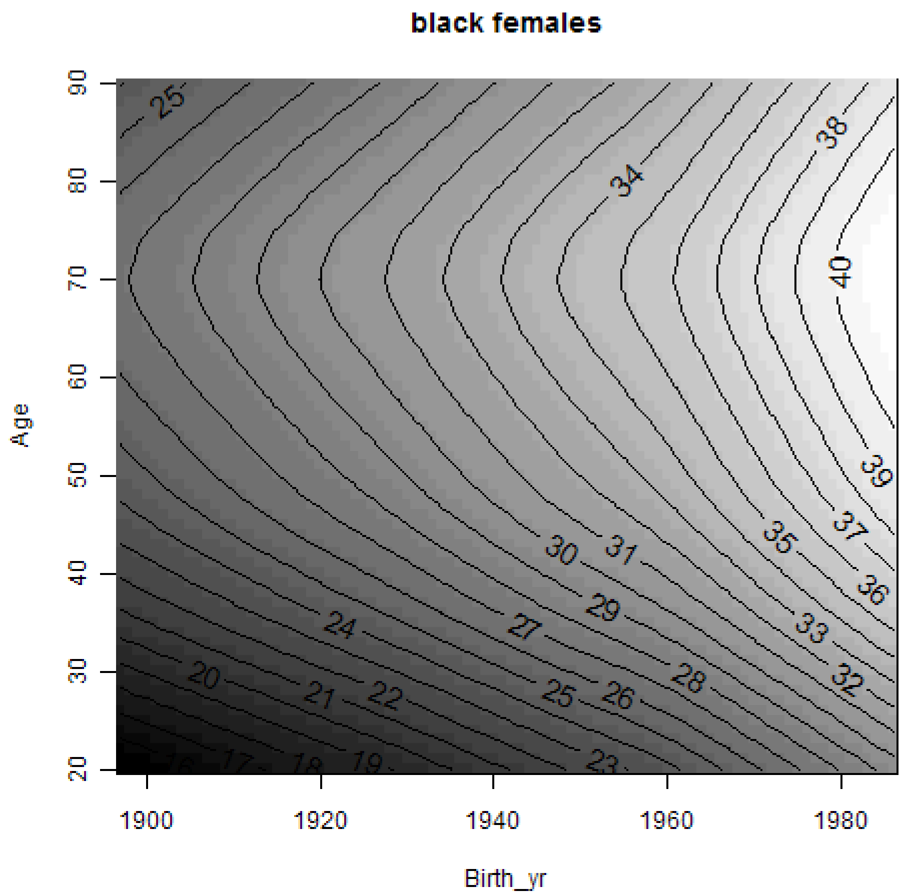
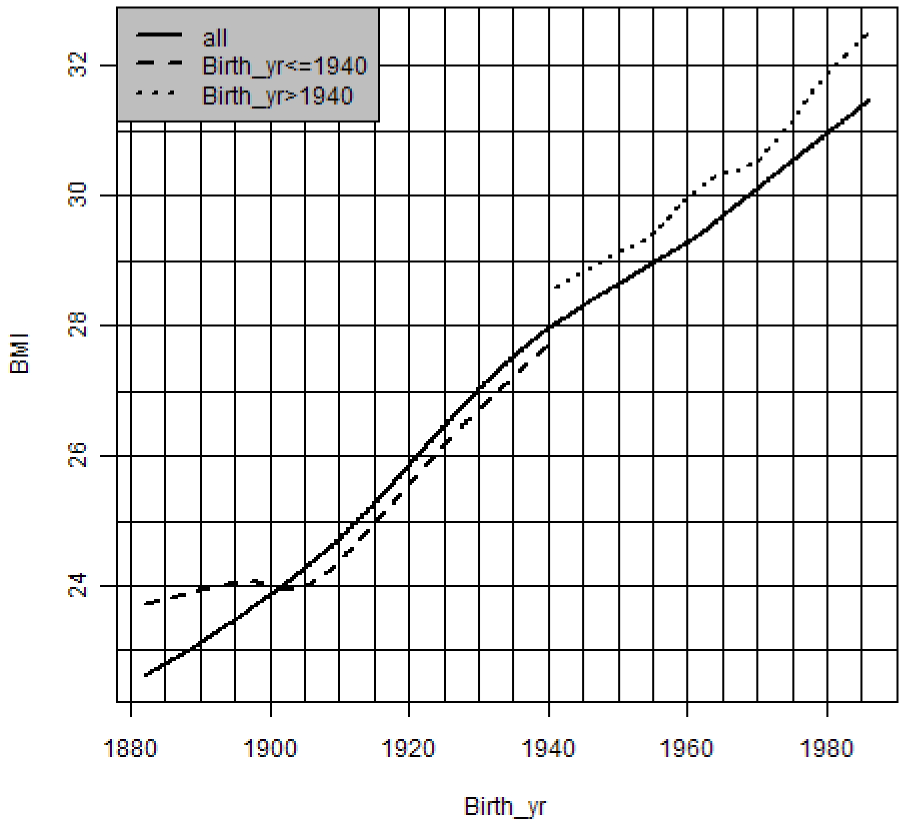


Figure 8. Trend of of BMI values of White Men estimated separately for before and after 1940 birth cohorts



Endnotes

---

[1] The upswing in excess weight is said to have begun in Australia in the 1970s (Norton et al., 2006).

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

[3] It is also seldom mentioned that the BMI values in the US are among the highest in the developed world (Komlos and Baur 2004).

[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.

[5] 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 are we consider the Current NHANES as one survey, making a total of 5 effective surveys.

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

[7] 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.

[8] About 4-5% of individuals with missing values are excluded from the analysis.

[9] Hence, there is no need to assume, for example, that the BMI values increased linearly or as a polynomial (Yatchew, 1998). The loess smoother is not fully determined, as the span has to be

set. The larger the span, the smoother the fit and vice versa, as in kernel smoothing. In fact, the span determines how many of nearest points are used in smoothing a particular observation, as a proportion of the sample size. The span was optimized over a set of discrete values via crossvalidation. Crossvalidation uses sums of squared residuals obtained from model fitted without an observation in question across all observations. The optimum span is 0.45, close to the default value of 0.5 provided in R. (Cleveland, 1979; Cleveland and Devlin, 1988). The same span was used for all of the estimates. We use the Akaika information criterion for model selection. AIC works better with GAM than does such alternatives as Nagelkerke's coefficient of determination. We also do bootstrapped estimation of confidence intervals (pointwise), although we do not report these for lack of space.

[10] (http://cran.at.r-project.org/), using the GAM package written by T. Hastie. GAM models have been used extensively in biology as a search in the *pub med* data base reveals. See, for example, Reolants, Hauspie and Hoppenbrouwers (2009). However, we were not able to find any publications that used GAM to estimate BMI trends.

[11] Admittedly PIR is not a perfect measure of real income insofar as it, for example, does not control for regional variation in housing prices and does not include such government transfers as food stamps. Nonetheless, it does control for household size and for inflation.

[12] We proceed as if it were distributed normally, without actually insisting on its normality. This leads to quasi-likelihood estimation (or generalized estimation equation).

[13] Residual RMSE was 4.6, 5.7, 5.7 and 7.3 for white male, white female, black male and black female strata, respectively. To be sure, the way we bootstrapped the data leads to a slight underestimation of the variability. In particular, in the bootstrap process, we took into consideration the survey weights, i.e. heteroscedastic variances, but not the correlations implied by the hierarchical, that is to say, the complex survey design. We believe that the major features

of the standard error are captured by our bootstrap procedure and hence that its results are suitable for the visual appreciation of the magnitude of the estimation error.

[14] We also estimated the model without the PIR and education effects to find that the difference in the results from the ones reported here is inconsequential. Hence, these are not included here for lack of space.

[15] In order to obtain a notion of the accuracy of the estimates, note that the bootstrapped estimates of the confidence interval was about 0.3 BMI points at age 30. We do not report these for the lack of space.

[16] 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.

[17] Ogden et al. (2007, 2008**)** have also noted that BMI values have not changed significantly in the most recent surveys**.**

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

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

[20] "The per-capita number of fast-food restaurants doubled between 1972 and 1997" (Chou et al., 2004, 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, Butcher and Levine, 2003).