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Cohort Analysis of Obesity: Trends by Education in the United States 1976-2014

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Short Abstract

Mid-aged low-educated White men have been identified at risk for multiple indicators of morbidity and mortality (Case & Deaton 2015), with clear cohort effects at play (Chauvel, Leist, Smith 2016). Testing another health risk factor, we use new age-period-cohort (APC) methods to detect cohorts and educational groups at particular risk of obesity in NHIS 1976-2014 (N=1,257,802): APC-Trend analysis to estimate slopes of obesity rates across cohorts, and APC-Gap analysis to estimate gaps between BA-holders and non-holders.

We detect steep increases in obesity rates and educational gaps in women from the 1960s cohort onwards. For men, both rates and educational gaps in obesity are linearly increasing across all cohorts under investigation.

While women born 1960+ show higher obesity rates and will likely be in higher need of obesity-associated social and healthcare than earlier-born cohorts soon, universal increases in obesity rates across all cohorts provide more support for the obesogenic environment hypothesis.

Extended abstract

Background

Since Case and Deaton's (2015) hallmark study, mid-aged low-educated White men have been identified at risk for multiple indicators of morbidity and mortality (1). We recently showed this to be a cohort effect, with sharply increased suicide mortality the 1960s cohort of White, low-educated and non-married men in 2010 (2). Obesity is another risk factor for falls, cardiovascular disease, diabetes, medical complications, and as such as risk factor for impaired health and associated with higher social and healthcare needs at older ages. Socioeconomic determinants in weight-height-ratio (Body Mass Index, BMI) and obesity have been well established (3–7). However, the causal effect of education on BMI is likely small and selection into higher education is more prevalent (8,9). Cohort analysis of obesity rates has rarely been carried out. Studies on obesity from a cohort perspective used age-period-cohort methods with problematic assumptions (10,11). The particular interest of investigating obesity from a cohort perspective is to identify social change across time (12). Studies from psychological and sociological perspectives have provided evidence that individuals, once overweight or obese, enter a vicious circle of stigma with associated challenges (failures) to maintain self-regulation and control of caloric uptake. Indeed, stigma has been put forward as fundamental cause of population health inequalities (13).

With obesity as risk factor of adverse health outcomes and increased need of social and healthcare when entering older age and interest in the detection of possible cohort effects, we use two advancements of age-period-cohort (APC) analysis to, firstly, detect development of obesity rates across cohorts, and, secondly, explore the development of the gaps in obesity rates between higher- and lower-educated men and women.

Method

Data

We use data of 1,257,802 participants (52.8% women) of the U.S. National Health Interviews Surveys (cross-sectional, annual data collection of the years 1976-2014. Five-year periods and five-year age groups 20-60 were the base of two new developments of age-period-cohort (APC) analysis.

Strategy of Data Analysis

The general purpose of age-period-cohorts models is to use a Lexis table (age x period) in order to decompose a dependent variable y into effects of age (α_a), period p (π_p) and cohort membership c (γ_c). Equation I specifies the linear composition of those effects:

Equation I

$$y^{apc} = \mu + \alpha_a + \pi_p + \gamma_c(APC)$$

Since cohort is a linear combination of age and period (c = p + a), the basic model cannot be solved. This identification problem is well known (14,15), and different attempts have been made to solve this problem (12,16). One solution to the problem of non-identifiability is to ignore the actual linear trends of age, period, and cohort, and introduced further constraints to detect deviations from those trends: This Age-Period-Cohort Detrended model has been applied to the detection of lucky (or protected) and unlucky (or disadvantaged) cohorts on outcomes such as political participation, income, and suicide mortality (2,17–19). The Age-Period-Cohort Detrended model posits the sum of age, sum of period, and sum of cohort trends to be zero, and the linear trends of age, period, and cohort to be zero (Equation II).

Equation II

$$\begin{cases} y^{apc} = \alpha_a + \pi_p + \gamma_c + \alpha_0 rescale(a) + \gamma_0 rescale(c) + \beta_0 + \varepsilon_i \\ \begin{cases} \sum \alpha_a = \sum \pi_p = \sum \gamma_c = 0 \\ Slope_a(\alpha_a) = Slope_p(\pi_p) = Slope_c(\gamma_c) = 0 \\ \min(c) < c < \max(c) \end{cases} \end{cases}$$

Analysis of obesity trends across cohorts. The Age-Period-Cohort Detrended model presented in Equation II has been further developed to overcome its unidentifiability of linear trends: The new Age-Period-Cohort Trended Lag (APCTLAG) model results from wisely adapting the different constraints to the model: The age linear trend is now constrained to the average within-cohort age effect. Further, the sum of age and period vectors are set to zero, and the period linear trend is set to zero. In doing this, the APCTLAG is now able to identify (linear) social change via the cohort vector (Equation III).

Equation III

$$
\begin{cases}
y^{apc} = \alpha_a + \pi_p + \gamma_c + +\varepsilon_i \\
\begin{cases}
\sum \alpha_a = \sum \pi_p = 0 \\
Slope(\pi_p) = 0 \\
Slope(\alpha_a) = \dfrac{\sum (y_{\mathrm{a+1,p+1,c}} - y_{\mathrm{a,p,c}})}{(\mathrm{p}-1)(\mathrm{a}-1)} \\
\min(c) < c < \max(c)
\end{cases}
\end{cases}
$$

The APCTLAG has been applied to age-period-cohort income analysis (18,20). The code is available in Stata (ssc install apcgo) (21).

Analysis of the development of inequalities (gaps) in obesity across cohorts. In order to arrive at a quantification of the gaps in obesity between different social groups (education, gender, race/ethnicity), we apply another method recently developed (20). The Age-Period-Cohort Gap/Oaxaca (APCGO) model also uses data structured in the Lexis table (age x period) in order to identify the trends across cohorts for two social groups (e.g. higher- and lower-educated individuals), and quantifies the gap between the two groups by the APCTLAG coefficient. Plotting the coefficient across cohorts depicts the inequalities across cohorts, their evolvement over time and the non-linear accelerations or decelerations in the cohort trend. To our knowledge, the APCGO is the only method currently available that is able to systematically quantify inequalities between social groups across cohorts.

The APCGO has been developed for a second purpose that will not be used here, namely to quantify the contribution of predictors/covariates to the dependent variable by decomposing the value of a dependent variable into explained and unexplained variance. This is done through the implementation of the Blinder-Oaxaca decomposition (20). The reason why no covariates are included here is the desire to maximize the time window of investigation. Any covariates whose measurement has changed across this time window cannot be meaningfully included into the analysis.

Results

Of the initial sample of 2,000,422 individuals with information on BMI and education, the first and last five-year age group needs to be omitted for age-period-cohort analysis. The final sample thus had 1,257,802 individuals, of which a total of 299,986 (23.84 %) reported holding a Bachelor's degree (BA) or higher degree and a total of 211,248 (16.8 %) reported a weight-height-ratio (BMI) of equal or more than 30 and were categorized as being obese.

Trend age-period-cohort analysis shows an almost flat trend across cohorts born before 1950 but substantial acceleration of obesity rates particularly for women born 1950 and later until the most recent cohorts under investigation (born 1985, Figure 1).

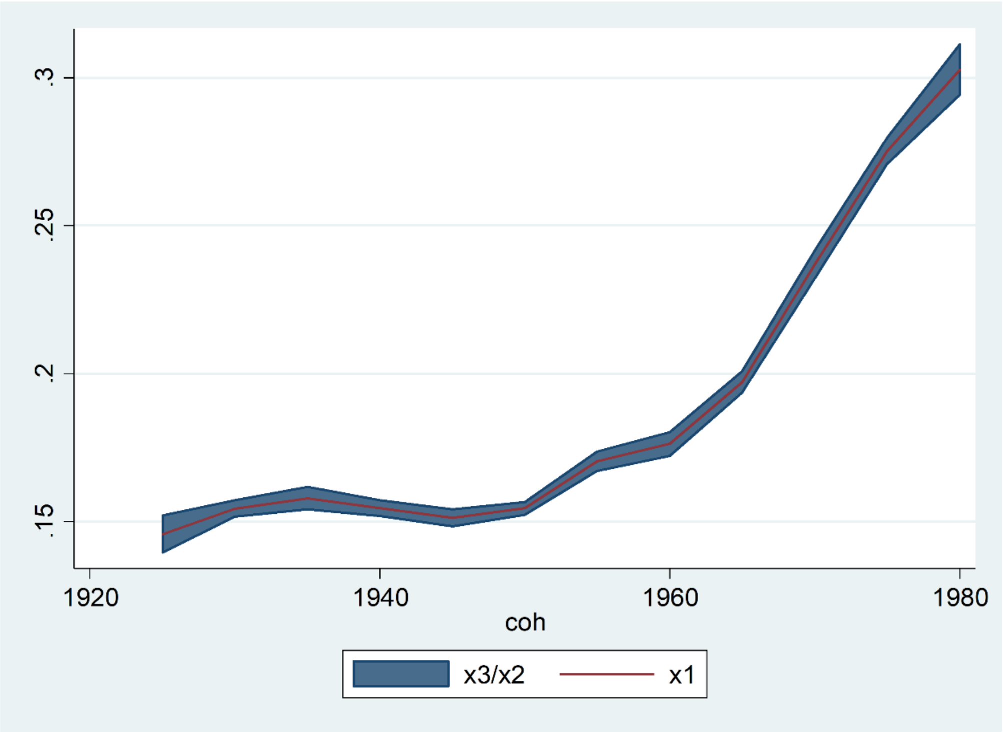

Figure 1. Obesity trends in women.

Educational gaps between BA-holders and non-holders are increasing in women, particularly from the 1960s cohort onwards. The steepness of the slope increases for cohorts born around 1960 and later (Figure 2).

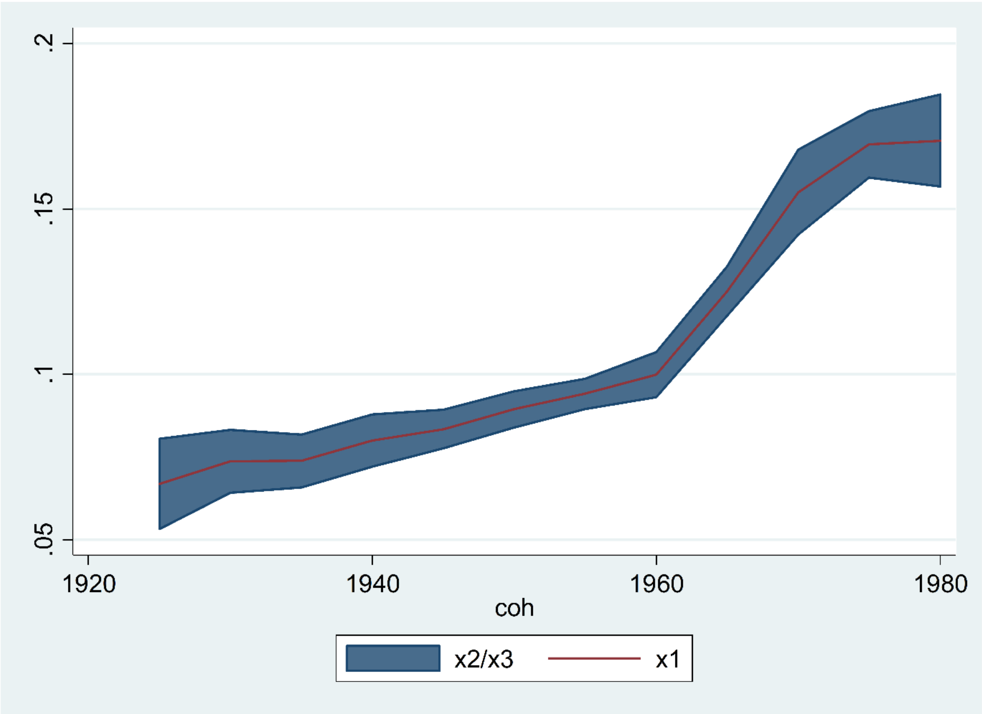

Figure 2. Educational gaps in obesity rates between female BA-holders and non-holders.

For men, both increases and educational gaps in obesity are increasing but similarly linear across all cohorts under investigation (Figures 3, 4).

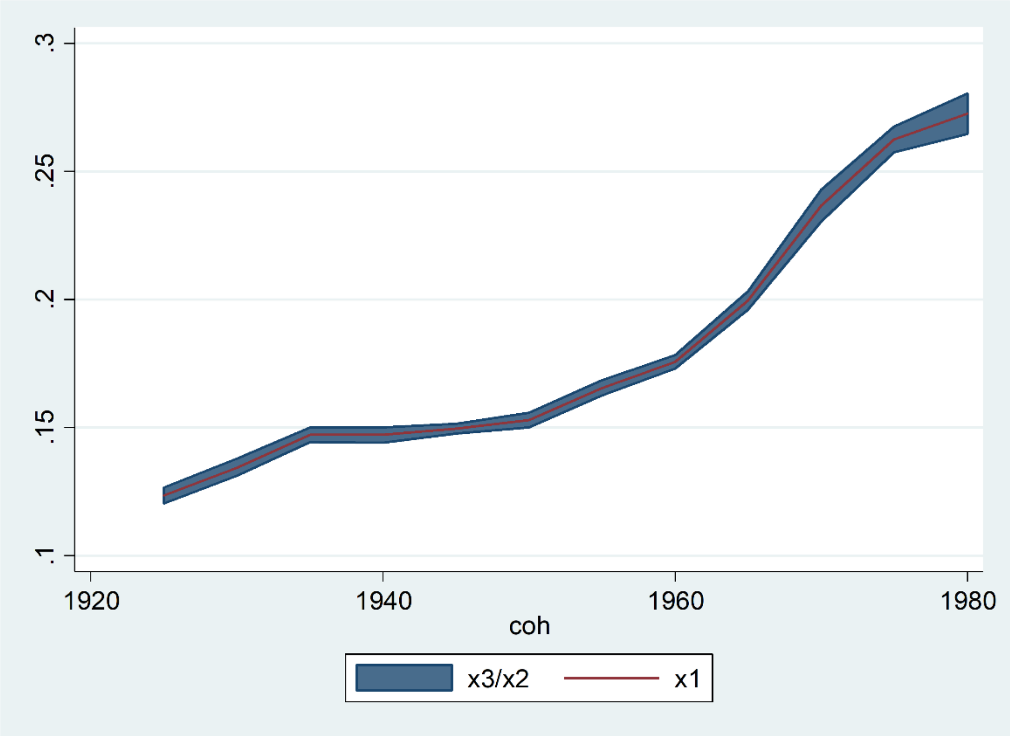

Figure 3. Obesity trends in men.

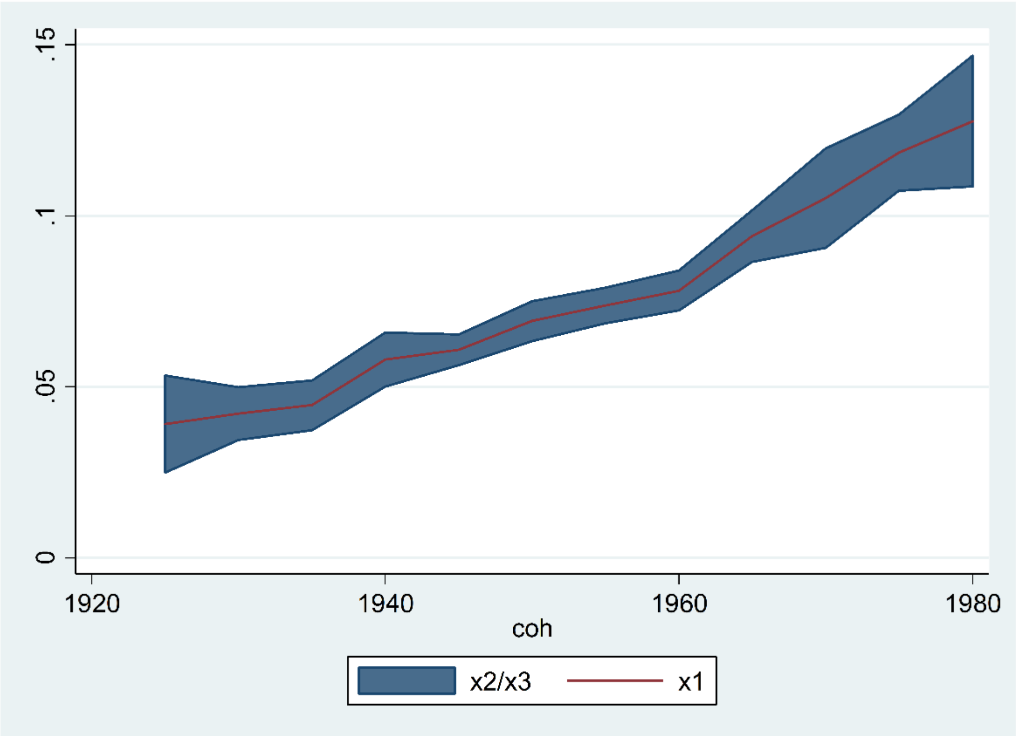

Figure 4. Educational gaps in obesity rates between lower- and higher-educated men.

Obesity rates for Non-Hispanic Whites are lower (14.8%) are lower than for Non-Hispanic Blacks (26.2%). Stratifying the sample by Black and White racial background and for higher- and lower-educated individuals, we see that the obesity trends in the overall sample are driven by the trends in lower-educated Black women and lower-educated White women (Figure 5), while divergent trends are visible in the stratified sample of men (Figure 6).

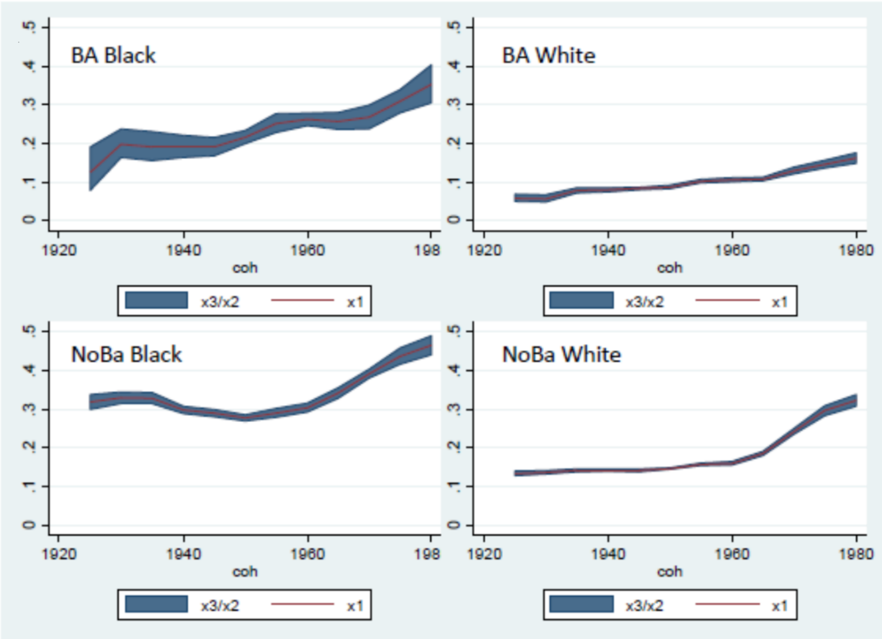

Figure 5. Trends in women by educational groups and self-reported racial background.

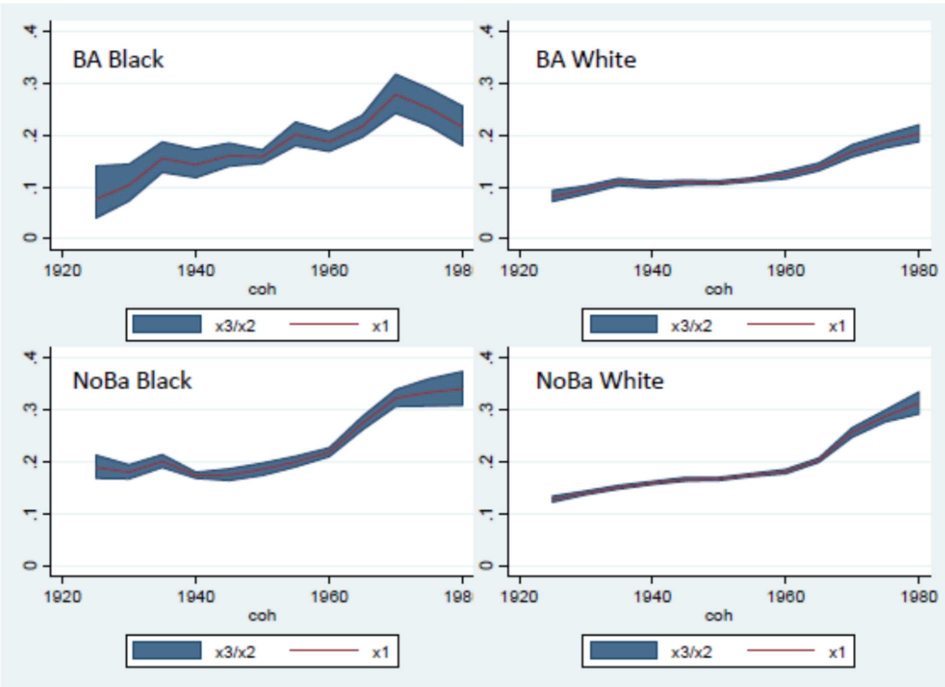

Figure 6. Trends in men by educational groups and self-reported racial background.

Testing the gaps in obesity rates between Black and White lower-educated women, the gap is smallest for the 1960s cohort (Figure 7).

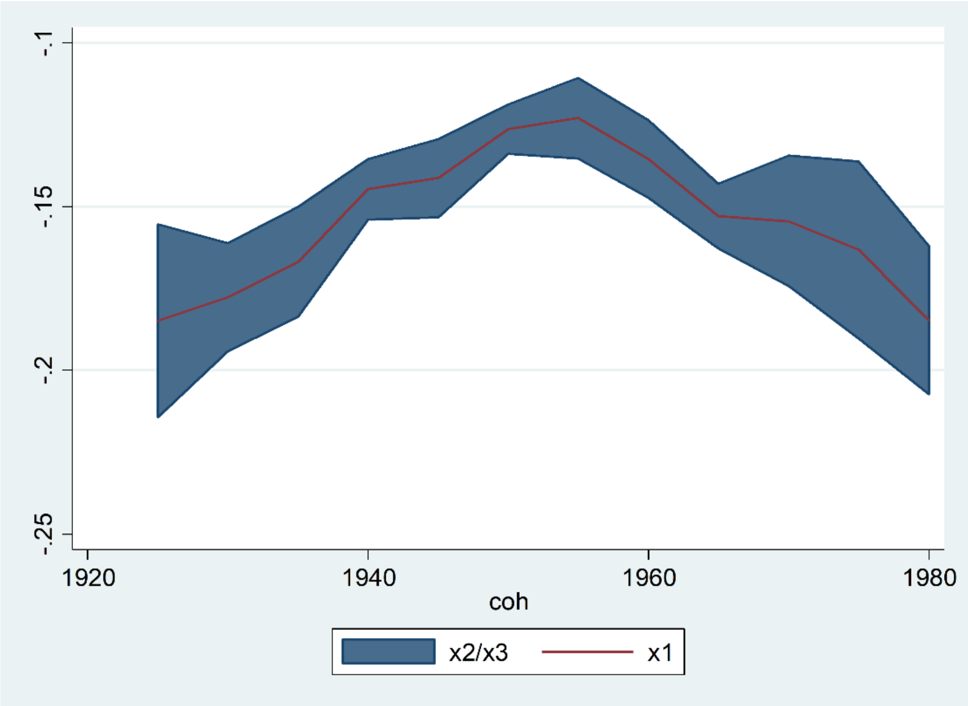

Figure 7. Gaps in obesity rates between lower-educated White and lower-educated Black women.

Discussion

From a cause-effect perspective, obesity is very likely not the underlying cause of obesity-associated health problems but more a surrogate of disadvantaged health conditions, e.g. the presence of metabolic syndrome (22). Since these health problems are the underlying causes of outcomes related to morbidity and healthcare needs, obesity interventions need to follow insights from tests of causality, not prediction (23). Nonetheless, cohort analysis of obesity presents the advantage of population-level assessments of risk of obesity-associated health problems and care needs due to the wide availability of BMI data across cohorts.

While women of the 1960s cohort now entering older age show indeed higher obesity rates and will likely be in higher need of social and healthcare than earlier-born cohorts in the coming years, the ongoing increases in obesity rates across all cohorts under investigation provide less support for a cohort effect and more support for the obesogenic environment hypothesis. This is in line with earlier analyses (24). Particular risk factors in the hypothesis of 'obesogenic environment' that have been put forward comprise increasing labor market participation of women (thereby having less time to prepare meals at home), availability and wide-spread use of high-calorie fructose syrup in drinks and pre-prepared meals, availability of fast food restaurants, availability of discounter supermarkets with little fresh and healthy foods, and changed food consumption patterns to eat outside one's home several times a day. The 1960s cohort, and particular its lower-educated members that have been identified at risk for multiple morbidity and mortality outcomes, is likely just the first to be systematically exposed to and affected by the obesogenic environment of today's societies since several decades.

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