Obesity from Childhood to Mid-Adulthood in the United States:

A synthetic cohort approach to measuring health trajectories

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Introduction

Obesity is one of the most concerning public health problems in the United States (US). Thirteen percent of children are estimated to have obesity before their sixth birthday; the prevalence of obesity is higher at every age thereafter, with 21% of school-aged children and 42% of adults having obesity in 2020.[1,2] These patterns are of concern because obesity is associated with poor health, especially cardiometabolic diseases.[3–8]

Population-based information about obesity dynamics from childhood through adulthood is scarce because there are very few studies following children for more than a few years. Some evidence of long-term growth patterns comes from longitudinal cohort studies in Europe.[9–11] Evidence from the US has been largely piecemeal, as there are few nationally representative longitudinal datasets, and those follow cohorts over a limited duration, covering segments of childhood. Consequently, obesity dynamics have only been described over short segments of the life course.[12–15] In fact, there is no single nationally representative dataset that tracks individuals from early childhood to adulthood in the US.

In this study, we apply a novel matching method to create a nationally representative dataset of obesity dynamics across the first four decades of life. We use data from two nationally representative cohorts, the Early Childhood Longitudinal Study, Kindergarten Class of 1998-9 (ECLS98) and the National Longitudinal Survey of Youth 1997 (NLSY97), to project weight trajectories to age 41 years, in 2035, for individuals born between 1991-4. Building on previous studies using synthetic cohort methods,[16] we estimate age-specific prevalence and incidence of obesity over the first four decades of life. Data on disease prevalence demonstrate the magnitude of the population affected by obesity. This is important, but insufficient: data on incidence is additionally necessary, as it makes it possible to identify the ages of highest risk and highest opportunity for prevention of obesity and its associated health consequences. Few studies have used an incidence-based approach due to limited data availability. The synthetic cohort approach demonstrates an expansion and leveraging of the existing data infrastructure to track weight patterns from childhood to adulthood and project health risks of young people into the future in the absence of nationally representative cohort data extending over the first decades of life; this approach will be even more important henceforth, as there are currently no nationally representative longitudinal studies of children in the United States today.

Methods

Data sources and study population

To create a synthetic cohort, we used two nationally representative longitudinal datasets that follow individuals over overlapping ages: the Early Childhood Longitudinal Study, Kindergarten Class of 1998-9 (ECLS98) and the National Longitudinal Survey of Youth 1997 (NLSY97).

The ECLS98 is a cohort study representative of the US Kindergarten cohort of 1998-99, implemented by the National Center for Education Statistics. Children from the birth cohorts of 1991-4 were sampled in Kindergarten (n=21,409). Data were collected in Kindergarten, Third, Fifth and Eighth grades.[17] Trained interviewers collected information from children, teachers and school administrators at schools; parents were interviewed over the phone.

The NLSY97 is a cohort study representative of US High-Schoolers in 1997, implemented by the Bureau of Labor Statistics. Civilian, non-institutionalized youths 12-16 years from the birth cohorts of 1980-84 were sampled in 1997 (n=8,984) and have been interviewed in person in 19 rounds until 2021, with annual (1997-2011) and biennial follow-ups (2011 onwards), including sociodemographic and health characteristics and information about their parents.[18]

Measures

We calculated body mass index (BMI) in each dataset. In ECLS98, weight and height were measured by trained staff using digital scales and ShorrBoards.[17] In NLSY97, weight and height were reported by participants.[18] Because people tend to underestimate their weight and overestimate height, we used for NLSY correction factors derived from NHANES, which contains both self-reported and clinically measured anthropometric data (See Rafei et al.).[19]

Matching Respondents Across Datasets

Steps are presented in Figure 1. We harmonized variables, pooled data, normalized the sample weights for the pooled dataset, and examined variable distributions. We used a mixed-effects modeling technique based on Cook's distance measure to identify impossible anthropometric outliers; these were re-coded as missing. We used linear interpolation to impute missing height and weight observations between study years, including non-survey years. In NLSY97, height was collected up to 2011, thus we replicated values from 2011, when participants were ~22 for subsequent years. We harmonized sociodemographic variables across cohorts at baseline: age, sex, race and mother's education.

To create a synthetic cohort, we matched respondents using a modification of the hot-deck imputation method developed by Little et al.[20] This method matches individuals from one dataset with complete information (donor) to a dataset of individuals with similar characteristics but with missing observations (recipient) and uses the information from the donor to impute the information in the recipient.[20] We followed the steps below to create the synthetic cohort.

Creating a donor and recipient dataset

We adapted the hot-deck imputation method to create trajectories, with data from the NLSY97 (participants moving from adolescence to adulthood) serving as "donor" data to provide future trajectories for the ECLS98 participants, which represent the "recipient" data. We treat the unobserved future BMI trajectories in ECLS98 as missing information and borrow information from NLSY97 to fill in these unobserved trajectories.

Computing summary statistics

We created a sub-setted pooled dataset from ages 10-17 years, the overlapping ages between the two cohorts. We kept individuals with at least two observations of BMI between ages 10-17 to estimate rate of change over time. Then, we stratified this sub-dataset by biological sex and fitted sex-specific simple linear mixed models of the form:

$$Y_{itd} = \beta_{0d} + \beta_{1d}t + b_{id0} + b_{id1}t + \varepsilon_{itd}$$
$$\begin{matrix} b_{id0} \\ b_{id1} \end{matrix} \sim N\left(\begin{matrix} 0 \\ 0 \end{matrix}, \Sigma_{bd}\right), \quad \varepsilon_{itd} \sim N(0, {\sigma_d}^2)$$

Here, Y_{itd} is BMI, $i = 1, ..., n_d$ indexes the individual in the donor $(d = 1)$ and recipient $(d = 0)$ group and $t = 1, ..., m_{id}$ indexes the observations associated with individual *i*. We then computed estimates of the individual-level BLUPs (Best Linear Unbiased Predictions) as $\begin{matrix} \hat{\beta}_{0id} = \hat{\beta}_{0d} + \hat{b}_{i0d} \\ \hat{\beta}_{1id} = \hat{\beta}_{1d} + \hat{b}_{i1d} \end{matrix}$, with associated variance-covariance estimate $\hat{V}_{id}$. An important aspect was the choice of *t*, for which we included all observations with overlapping ages, which are the maximum ages in the younger cohort and the minimum ages in the older cohort.

Matching donors and recipients

We matched a set of donor individuals to each recipient based on subject-level trajectories estimated through simple linear mixed models. From these models, we extracted the coefficients (intercepts and slopes) for each person to build the matching models. We matched BMI trajectories in ECLS98 with the most similar BMI trajectories from NLSY97 at ages 10 to 17 years. We used a Mahalanobis distance measure, which re-scales distance by variance, to determine potential matches. For each person in the recipient dataset, $i = 1,...,n_0$, we computed the Mahalanobis distance between that individual and the individual *j* in the donor set:

$$d_{ij} = \left(\hat{\beta}_{0i0} - \hat{\beta}_{0j1} \quad \hat{\beta}_{1i0} - \hat{\beta}_{1j1} \right) \hat{V}_{i0}^{-1} \begin{pmatrix} \hat{\beta}_{0i0} - \hat{\beta}_{0j1} \\ \hat{\beta}_{1i0} - \hat{\beta}_{1j1} \end{pmatrix}$$

The first matching model used a 1:1 ratio of closest matches (one donor per recipient) with replacement, because there were more recipients than donors. The second matching model used a 5:1 ratio (five donors per recipient), which is preferred because it integrates uncertainty in the projected trajectories. Matching was based on BMI at baseline, rate of change in BMI over time (age), and sex.

In separate models, with a 5:1 ratio, we added race and mother's education as additional matching variables, to examine the possibility that race and education groups might have differing BMI trajectories. We used three matching models: Model 1) matching conditional on BMI at baseline, rate of change in BMI, and sex; Model 2) matching on Model 1 characteristics plus race; and Model 3) matching on Model 2 characteristics plus mother's education. The additional variables did not improve or modify the balance between donors and recipients. This finding indicates that children in these different groups do not have systematically different growth patterns, after considering their BMI trajectories between ages 10-17 years. Also, adding more matching variables made the differences (distance) between intercepts and slopes wider for each set of matched individuals, because the model must go further afield to find matches meeting the multiple criteria, resulting in a higher number of unmatched donors. Therefore, Model 1 was preferred.

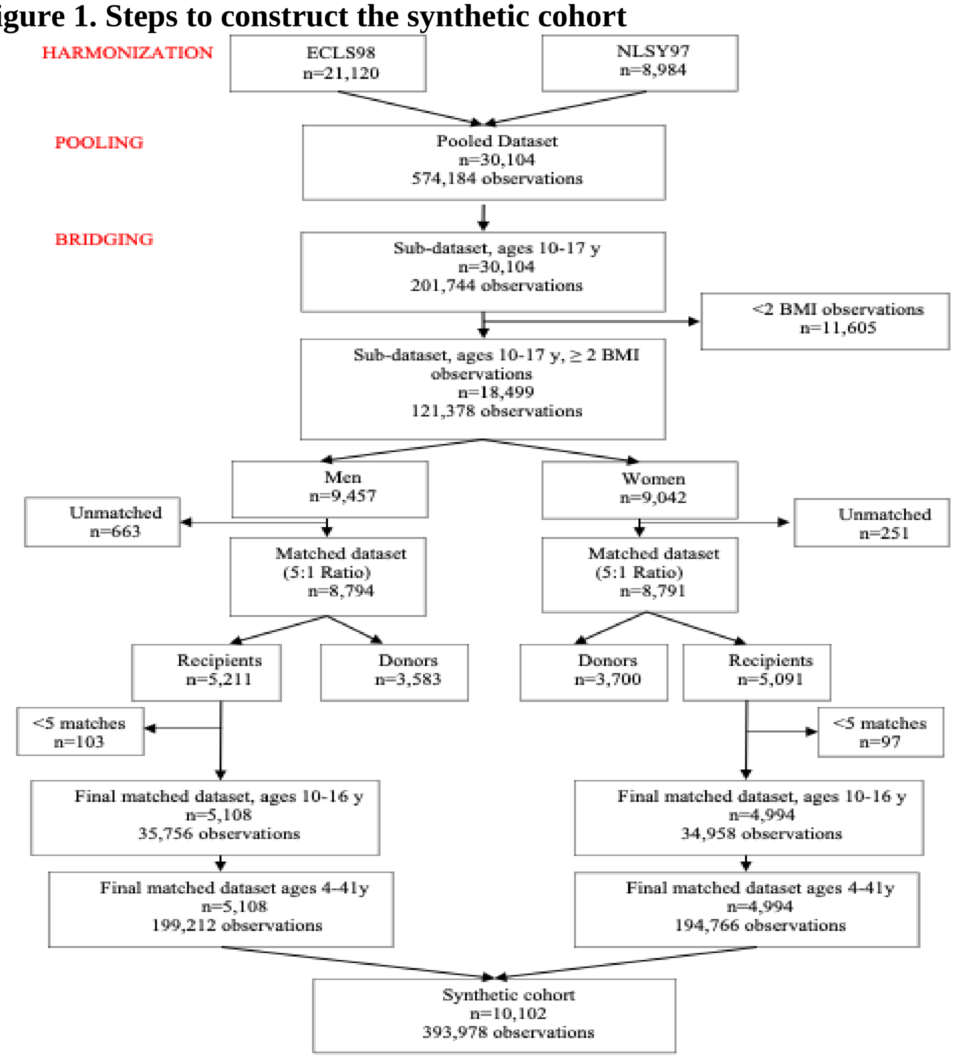
As a robustness check, we tested different tolerance windows to determine the maximum acceptable distance between donor and recipient trajectories. We compared models with no maximum established versus models with a maximum of 3, 2, and 1 BMI units in the intercepts and 0.3, 0.2, and 0.1 BMI units in the slopes. As the tolerance values decreased, the distances between mean BMI at baseline and over time were closer but a higher number of individuals were unmatched. We selected a tolerance of 2 and 0.2 BMI units in the intercepts and slopes, respectively, as this tolerance keeps a close distance between donors and recipients and retains a high number of matches. After applying the tolerance values, not all recipients had five pairs of matches because some children had a high BMI at baseline or a high rate of change of BMI over time. We removed individuals from the recipient dataset who were not selected as matches or who had less than 5 matches. As less than 1% of the sample could not be matched, the impact of these cases on the analysis is minimal.

Linking donor and recipient trajectories

In matching, we assumed that each 5-1 set of donors-recipient had similar BMI trajectories and could be combined as single individual trajectories. For each set, we linked pairs of donor and recipient trajectories using the closest BMI observations at the end of the recipient trajectory (ECLS98) with the first observation for each donor trajectory (NLSY97). When there were duplicated ages in the donor and recipient datasets, we used the last observation from the recipient dataset to link to the subsequent age in the donor dataset and removed duplicated ages in the donor trajectory. When there were no overlapping ages, we used linear interpolation to fill in the missing observations between the two trajectories, assuming a linear rate of change in BMI, given the short time of < 4 years between measurements.

From the original pooled dataset, we appended the entire information of the matched trajectories at ages 10-17 to obtain a synthetic cohort with BMI trajectories from ages 4 to 41 years, the age range in the original datasets. We projected trajectories to age 41 years, in 2035, for boys and girls who were actually observed up to 2007 (mean age 13.5 years).

Figure 1. Steps to construct the synthetic cohort



Statistical analysis

We used the survey design (weights, clustering, and stratification) of the recipient dataset at baseline and replicated across all data points. We applied Rubin's rules[20] for combining the multiple imputed estimates of the five sets of trajectories per person to obtain corresponding pooled estimates and standard errors.

We used the synthetic cohort to estimate mean BMI and the prevalence of obesity over time - defined as the proportion of children with obesity at each age. Obesity in children and adolescents was defined as BMI >= 95th percentile using the U.S. sex- and age-specific growth charts.[21] Obesity in adults (age >=20 years) was defined as BMI >= 30 kg/m^2.

We calculated age-specific incidence rates as the number of new cases of obesity at each age divided by the number of person years of follow-up (PY) contributed by individuals without obesity (person-years at risk). Individuals with obesity at any previous age were excluded from calculations for subsequent ages because they were not eligible for incident obesity, expressed as rate per 100PY. The follow-up period was defined as half of the time between each age and the following age for an incident case, or the entire time between these 2 ages if the person remained without obesity, assuming that the obesity threshold is crossed at the midpoint between the two ages.[22]

To check external validity, we compared the mean BMI trajectories in the synthetic cohort to the observed estimates from the same birth cohorts from nationally representative cross-sectional data from the National Health and Nutrition Examination Survey (NHANES, 1999-2018)[23]. We also compared the synthetic cohort with data from the same ages in the most recent NHANES

(2017-2020),[24] to see whether the birth cohort of 1991-94, under study here, is expected to have higher, lower, or similar weight trajectories as previous cohorts.

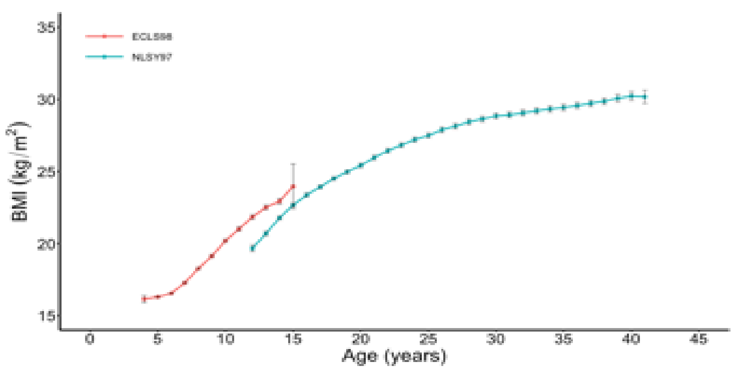
Results

Pooled dataset

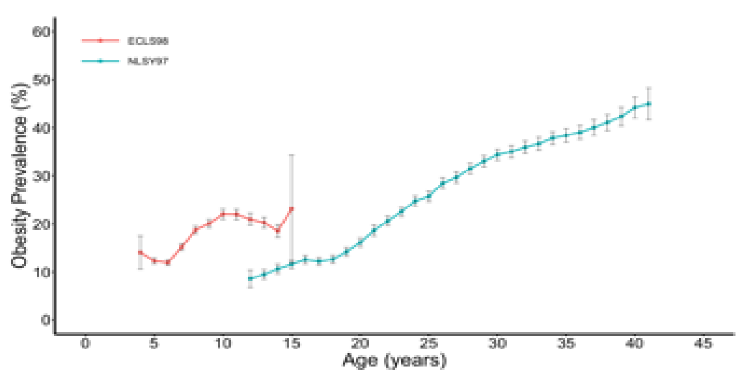
The pooled dataset consists of 30,104 individuals with 574,184 observations. Figure 2 presents the observed mean BMI trajectories and age-specific obesity prevalence in each original dataset. Mean BMI increased with age. During the overlapping ages of 12-15 years, the prevalence of obesity was higher in the 1991-4 birth cohort compared to the 1980-4 birth cohort.

Figure 2. Body mass index (BMI) and obesity prevalence over time by cohort

A)



B)



A. Observed mean BMI at ages 4 to 41 years.
B. Age-specific obesity prevalence at ages 4 to 41 years.
Data: ECLS98, born between 1991-94 and NLSY97, born between 1980-84.

Mixed models

Table 1 shows summary statistics of simple linear mixed models of BMI at ages 10 to 17 years in the pooled dataset. There are differences in the mean BMI at baseline and in the mean change in BMI for each one-year of age between individuals and within individuals. The covariance between intercepts and slopes showed that there is a strong inverse correlation between BMI at baseline and BMI change over time: children with higher BMI at baseline tended to gain less weight over time.

Table 1. Summary statistics of linear mixed models of BMI among boys and girls aged 10-17 years, a pooled analysis of two nationally representative cohorts in the United States

	Boys			**Girls**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Fixed Effects						
Intercept	11.73	11.50 – 11.96	**<0.001**	12.77	12.54 – 13.00	**<0.001**
Slope (Age)	0.77	0.75 – 0.79	**<0.001**	0.72	0.71 – 0.74	**<0.001**
Correlation fixed effects	-0.904			-0.904		
Random Effects						
σ^2	0.86			0.86		
τ_{00}	91.03 $_{\text{IDs}}$			88.49 $_{\text{IDs}}$		
τ_{11}	0.47 $_{\text{IDs.Age}}$			0.49 $_{\text{IDs.Age}}$		
ρ_{01}	-0.87 $_{\text{IDs}}$			-0.87 $_{\text{IDs}}$		
ICC	0.97			0.97		
N	9457 $_{\text{IDs}}$			9042 $_{\text{IDs}}$		
Observations	38182			36295		
Marginal R^2/ Conditional R^2	0.103 / 0.971			0.092 / 0.970		

Results of fitting simple linear mixed models (fixed and random effects) of body mass index (BMI) from ages 10 to 17 years among boys and girls across cohorts. We examined BMI differences between individuals and within individuals at baseline and over time. Data: ECLS98) and NLSY97.

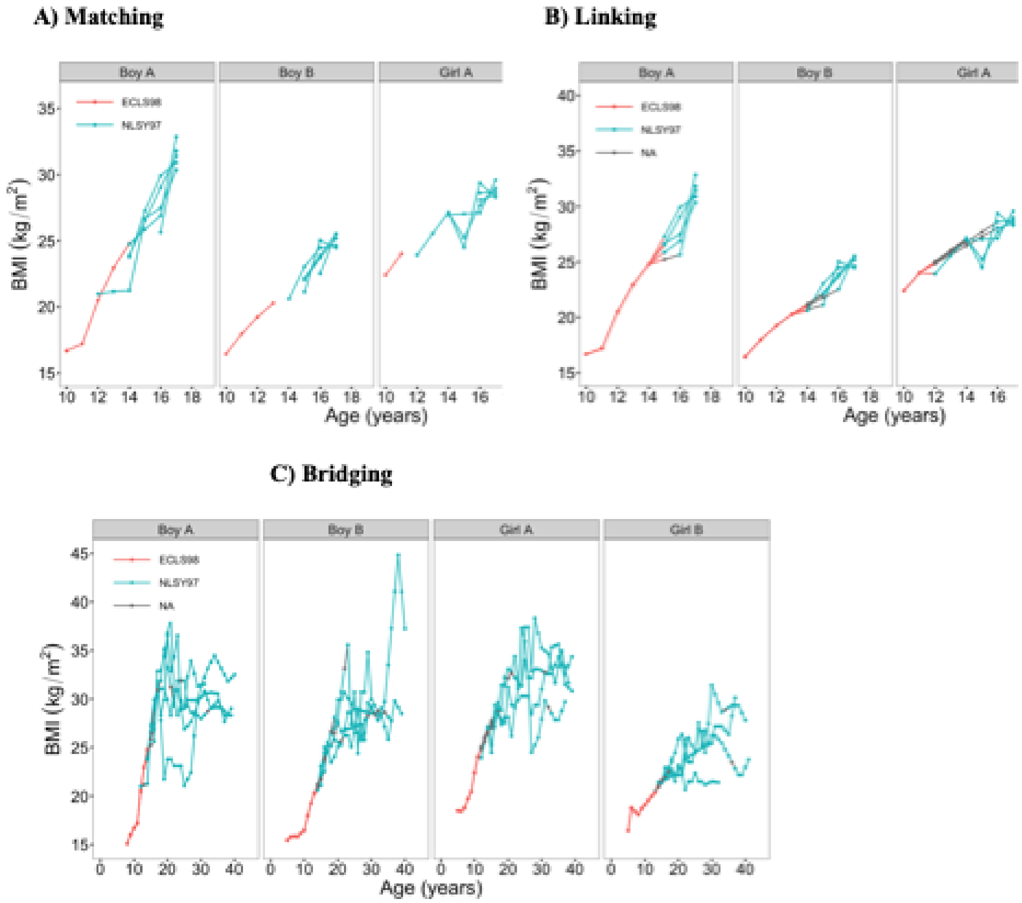
Matching

Figure 3 Panel A shows a visualization of BMI trajectories of the five donors per recipient in two boys and two girls selected randomly. For each set of donor-recipients, the five matched donors had similar BMI trajectories. There were differences in BMI at baseline given differences in age at which the first observation was available in the older cohort. For example, in Boy A, the five donor trajectories differed at baseline, with one trajectory starting at age 12, three at age 14, and one at age 16.

Linking and bridging donor and recipient trajectories

Figure 3 Panels B and C present a visualization of the linkage and bridging of five donor trajectories with the corresponding matched recipient trajectory among two boys and two girls. Panel B shows the linkage of BMI trajectories in the subset of individuals aged 10 to 17 years. Panel C shows BMI trajectories after appending the entire information from ages 4 to 41 years. In some individuals, the five donor trajectories differ as individuals grow older, highlighting the importance of capturing this uncertainty via the 5:1 ratio matching. There are also differences in the length of follow-up due to age differences at study entry and attrition.

Figure 3. Visualization of matching, linking, and bridging donor and recipient datasets

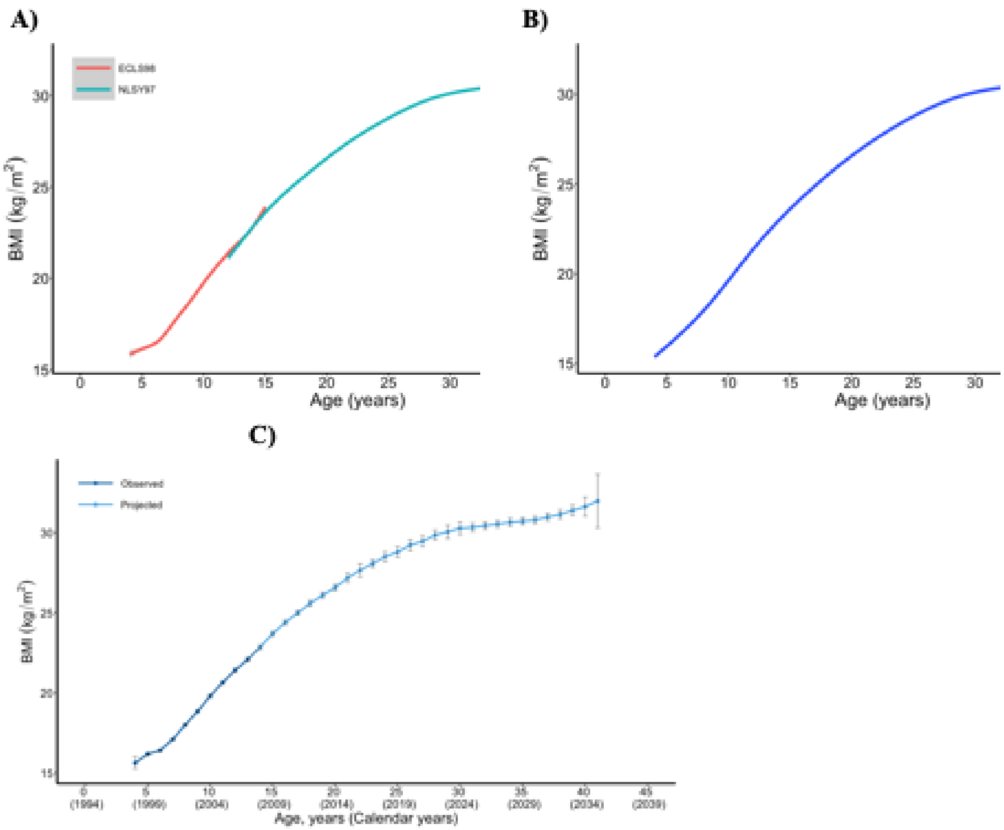


A. Graphic visualization of matching 5:1 ratio, five donors (NLSY97) for each recipient (ECLS98). Matching criteria were BMI at baseline (intercept), annual rate of change in BMI at ages 10-17 years (slope) and sex (stratified models).
B. Linkage of each set of matched individuals, donors (NLSY97) and recipients (ECLS98) at ages 10 to 17.
C. Full trajectories from ages 4 to 41 years after appending the whole information from each donor-recipient set of matches. For visualization purposes, we selected two individuals at random for each sex. NA=missing observations; we used simple linear interpolation to fill in these missing values between the donor-recipient trajectories.
Data: ECLS98, recipient dataset and NLSY97, donor dataset.

Weight patterns and prevalence and incidence of obesity in the first four decades of life

Figure 4 shows smoothed trajectories of BMI and survey-weighted age-specific mean BMI in the bridged synthetic cohort. Panel A shows that BMI trajectories overlap between the original cohorts at ages 12 to 15 years, indicating that the matching procedure is working well. Panel B presents the mean BMI trajectory of the synthetic cohort of 10,102 individuals with 393,978 observations spanning ages 4 to 41 years who were born in 1991-4. Age-specific estimates are calculated from combining the five trajectories. Panel C shows that mean BMI increased steadily with age, from 15.6 kg/m^2 at age 4 to a projected 26.1 kg/m^2 at age 19. In adulthood, the mean BMI is projected to increase with age at a slower pace, from 26.6 kg/m^2 at age 20 to 32 kg/m^2 at age 41. When we compare BMI trajectories from the synthetic cohort to observed cross-sectional estimates from nationally representative data in NHANES for the same cohort, the mean BMI at each age and calendar period were within 1%.

Figure 4. Age-specific BMI derived from the synthetic cohort



A. Smoothed unweighted BMI trajectories by original study (donor and recipient cohorts).
B. Smoothed unweighted BMI trajectories from the synthetic cohort of individuals aged 4 – 41 years. **C.** Weighted age-specific mean BMI from the synthetic cohort, ages 4 – 41 years.
Data: ECLS98 and NLSY97

Figure 5 Panel A shows obesity at ages 4 to 41 years. The prevalence of obesity increased across elementary school years from 10.0% at age 4 to 19.9% at age 11. In adolescence, it is projected to remain stable, staying steady from 19.0% at age 12 to 19.3% at age 18, but followed by an increase to 21.5% at age 19. From age 20 onwards, the prevalence of obesity is projected to continue to increase yearly, reaching 56.3% at age 41 in 2035.

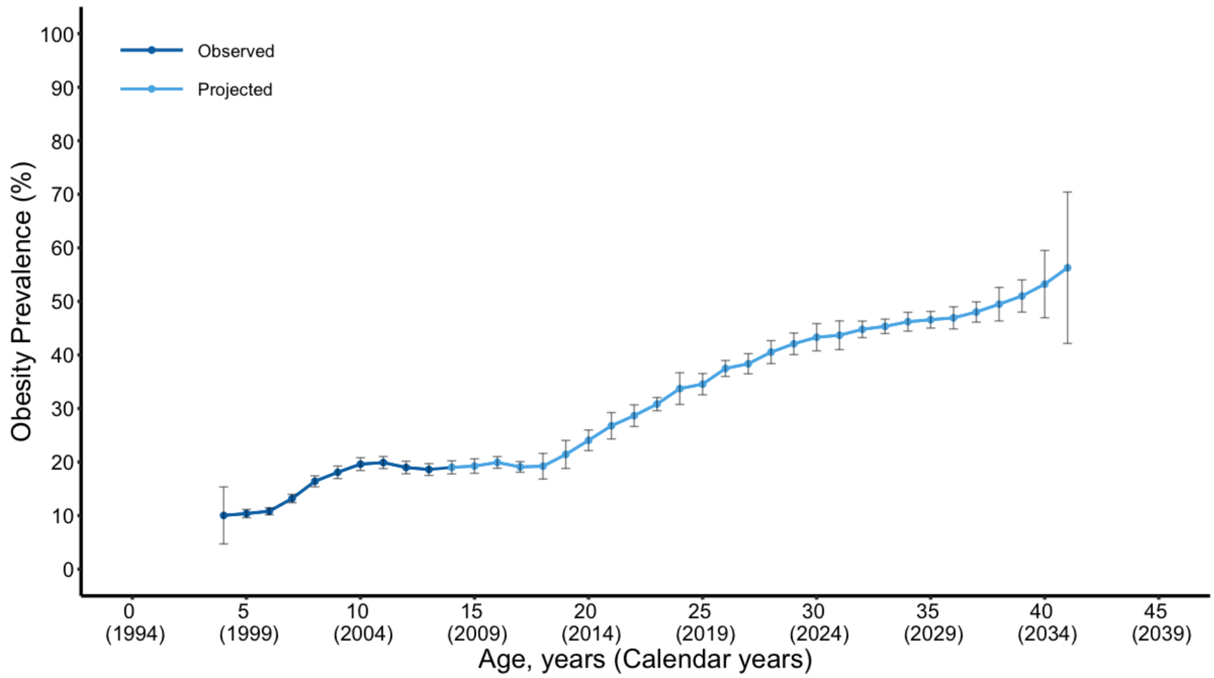
Boys and girls had similar obesity prevalence at ages 5 to 7, but, from age 8 onwards, boys developed more obesity, a trend that remained constant through adolescence, but which is projected to reverse at age 19, when women will have a higher prevalence of obesity; the differences between sexes are projected to increase, with obesity prevalence at age 41 reaching 60.7% for women and 52.6% for men.

Figure 5 Panel B compares age-specific obesity prevalence between the synthetic cohort and people of the same age from the latest cross-sectional nationally representative data (NHANES, 2017-2020). Obesity prevalence patterns in the synthetic cohort are within the confidence intervals of NHANES estimates. Prevalence in the synthetic cohort tended to be lower than NHANES from ages 4 – 23 and higher from age 28 onwards. Thus, the birth cohort of 1991-4 is expected to surpass today's cohorts of 40-year-olds in obesity by as much as 10 percentage points when they reach the same age.

Figure 5 Panel C shows obesity incidence rates from ages 4 to 41 years. The age-specific incidence of obesity was 2.24 new cases (0.00-6.60) per 100 person-years (PY) at age 5 and increased during childhood, reaching the highest value at age 8 at 4.00/100 PY (3.29-4.73). In later childhood and early adolescence (ages 9-12), incidence declined, reaching a nadir of 1.10/100 PY (0.69-1.51) at age 12. During the first half of adolescence, ages 12-15, incidence rates are projected to oscillate between 1 and 1.5/100 PY. At age 16, the incidence of obesity is projected to start increasing again, reaching a peak value of 4.48/100PY (3.04, 5.92) at age 26. Thereafter, obesity incidence is projected to oscillate around 1 to 3/100 PY, with another incidence peak at age 38 at 3.60/100 PY (0.00, 8.91).

Figure 5. Age-specific obesity prevalence and obesity incidence in the synthetic cohort

A)



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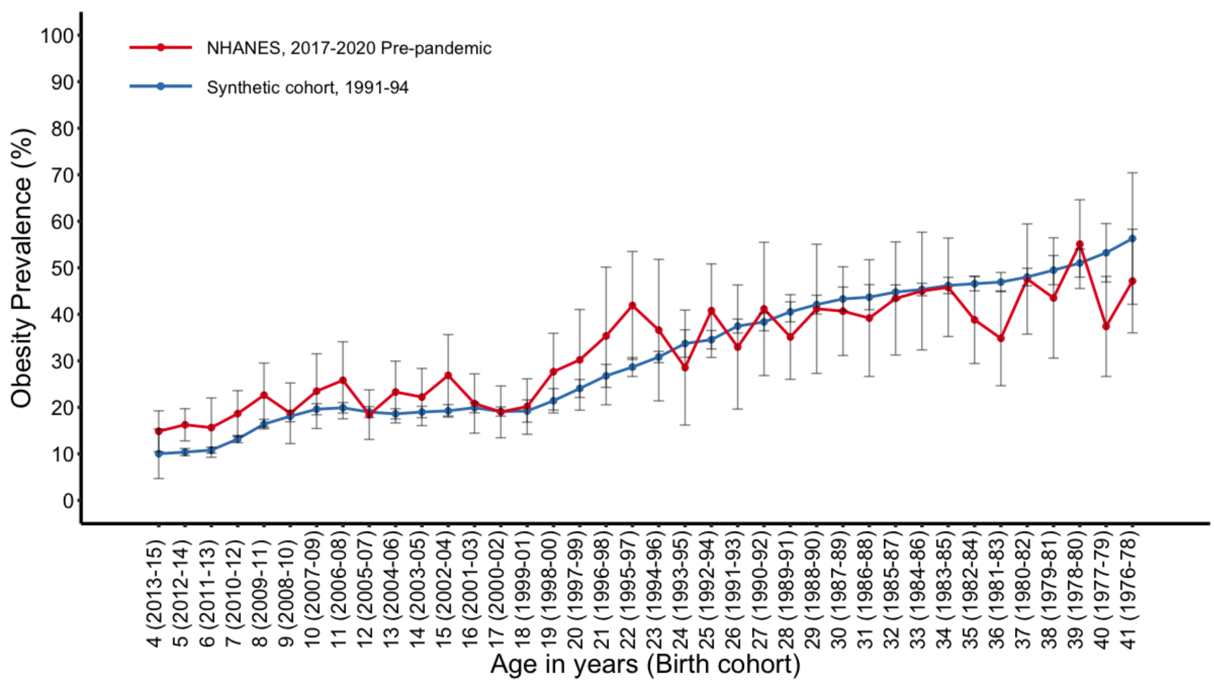

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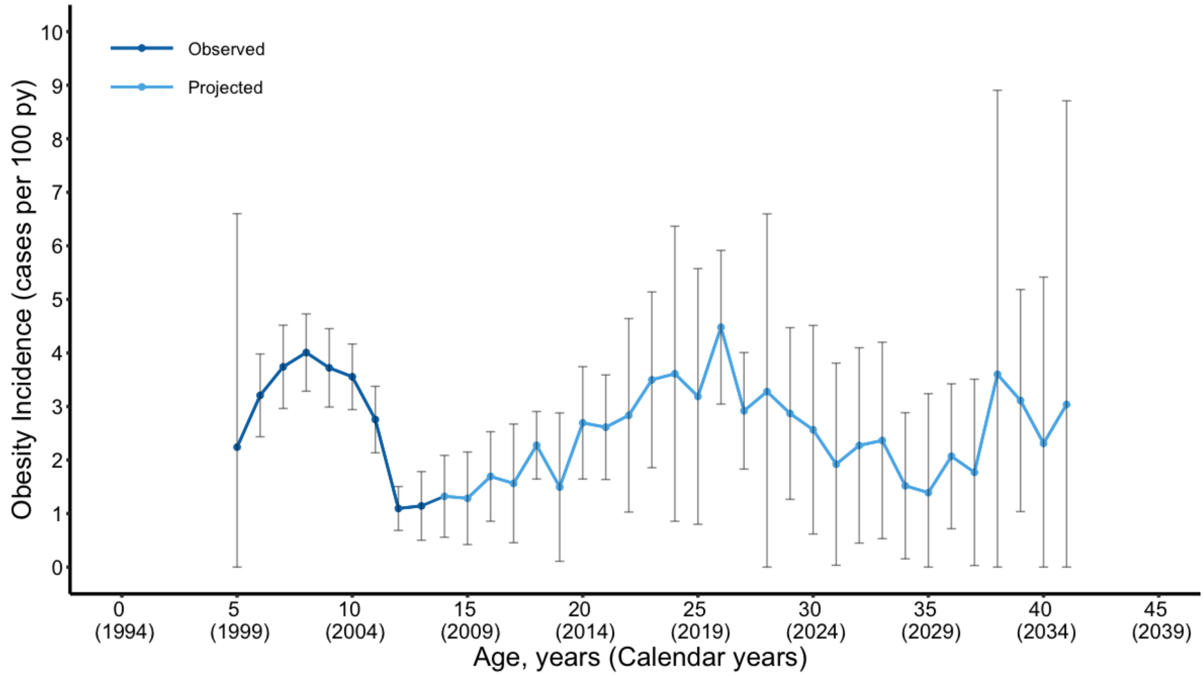

A. Age-specific obesity prevalence at ages 4-41 years, with projections spanning from 2008-2035.
B. Comparison of age-specific obesity prevalence at ages 4-41 years estimated from the synthetic cohort and from the latest cross-sectional nationally representative data, NHANES.
C. Age-specific obesity incidence rate (cases per 100 person-years) from ages 4-41 years, projections spanning from year 2008-2035.
Data: Synthetic cohort of individuals born in 1991-94; the National Health and Nutrition Examination Surveys (NHANES), 2017-2020 Pre-pandemic covering birth cohorts from 1976-2015.

Discussion

Obesity dynamics early in life are important for long-term health, but have only been described piecemeal, because nationally representative cohorts are few and have limited follow-up duration. We created a nationally representative synthetic cohort spanning the first four decades of life and showed how weight changes across the first half of the life course. Mean BMI increased from 15.6 kg/m^2 at age 4 to 32 kg/m^2 at age 41. The U.S. birth cohorts of the early 1990s had on average a healthy weight in early childhood, but by the time they reach age 29 years, the cohort is projected to have an average BMI corresponding to obesity.

Excess weight is already observed at young ages, with 2.24 new cases of obesity per 100 PY at age 5 and 4/100 at age 8. Consequently, the prevalence of obesity doubles between ages 4 and 11 years, from 10.0% to 19.9%. The rate of incidence of new cases is relatively low at ages 9-12 oscillating at 1-1.5/100 up to age 15, but new cases tick up again from age 16, peaking at 4.48/100 at age 26. Consequently, the prevalence of obesity stabilizes in early adolescence but then increases during the transition into adulthood. During the late 20s and 30s, the incidence of new cases oscillates around 1-3/100 and peaks again in the late 30s at 3.60/100. Thus, by their early 40s, more than half of the cohort is expected to have obesity. Previous simulations from U.S. cohort data have similarly anticipated increases in the future prevalence of obesity into adulthood for contemporary youths.[16]

Comparing the synthetic trajectories of the 1991-4 birth cohort with cross-sectional data from older birth cohorts passing through the same age ranges today, this younger cohort has lower BMI up to age 23 years but is projected to increase in weight from age 28 onwards. These differences suggest that the cohort born in 1991-4 will have even higher obesity than current cohorts, born in 1976-9, had at the same age. Thus, the projections indicate that obesity is not slowing down, and that today's cohorts of young adults will experience the health consequences of obesity even more than previous cohorts.

Males and females showed different patterns of obesity, consistent with previous studies,[16,19] with higher obesity among boys in middle childhood and adolescence but higher obesity for women starting in the transition to adulthood - a difference that becomes wider in their 30s. Sex-based dimorphism in body weight is recognized as the result of hormonal regulations as well as life events, especially motherhood.[2526–28]

Incidence patterns showed an inverted U-shape of new cases during childhood, peaking at age 8 at levels much higher than at younger and subsequent ages. This peak in new cases of obesity corresponds with the period of adiposity rebound documented around age 6.[29–31] Increases in new cases are expected in late adolescence and adulthood, with peaks at ages 26 and 38. There have been few reports on obesity incidence across adolescence and early adulthood, and the incidence peaks have not been reported previously.[32] Throughout young adulthood, people become independent from their parental home, move to college, start working, become parents - events that may be linked with obesity onset.[33]

We applied methods similar to Ward et al.[16] to combine, across datasets, trajectories of individuals matched on their growth patterns. While Ward et al. focused on projections of obesity prevalence at age 35 years, the present study provides age-specific weight trajectories, obesity prevalence and obesity incidence rates over the first four decades of life. In matching, we assumed that the older cohort could donate information to the younger cohort based on similar biological characteristics - sex and weight trajectories at overlapping ages. Thus, even if there are differences in level of BMI and obesity across cohorts, a person of a given BMI, wherever they are on the distribution in their own cohort, will have similar BMI trajectories to a person in another cohort with similar weight trajectories in the overlapping age period. A possible limitation is that it could be that BMI trajectories beyond age 17 are different despite similarities at younger ages. To reduce this concern, we matched the five closest donors for each recipient and averaged estimates of these for each trajectory, thus introducing variability; still, the possibility of systematic differences remains. Another possible limitation could be that sociodemographic characteristics modify weight trajectories over time. To address this concern, we examined matching models conditional on race and mother’s education. Adding these variables did not improve the balance between donors and recipients, nor made the distances between matches closer, suggesting that the impact of social characteristics is already captured in children's growth trajectories at ages 10-17, and differences in growth between social groups are not additionally divergent. A separate limitation, typical of longitudinal studies, is that not all trajectories span the same age ranges due to age differences at enrollment and loss to follow-up, creating more uncertainty in estimates at ages 4 and 41 due to smaller sample size at these ages. Additionally, we note that data are from before the COVID-19 pandemic, which may have distorted weight patterns and increased BMI;[34–38] If so, these projections may be under-estimates of future obesity trends.

This study presented a synthetic cohort following a birth cohort of the early 1990s to the projected age of 41 and therewith estimated trajectories of incident and prevalent obesity. Projections until 2035 show continuing increases in mean BMI and obesity across the first half of the life course, suggesting that today's cohorts of young adults will experience even more exposure to obesity than older contemporary cohorts. We identified peaks in obesity incidence in middle childhood and the mid-twenties, with some indication of an additional peak in the late 30s. These are therefore ages of highest risk but also highest opportunity for prevention or delay of obesity health complications. The synthetic cohort method applied here is a novel approach that can be replicated to make efficient use of existing data infrastructure. It demonstrates new opportunities to study health over the life course and to monitor changes in population health, even in the absence of nationally representative longitudinal studies of children born in the United States in this century.

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