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Intergenerational Profiles of Socioeconomic (Dis)advantage and Obesity During the Transition to Adulthood

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Abstract

Investigations of socioeconomic status (SES) and health during the transition to adulthood in the United States are complicated by the later and more varied transitions in residence, employment, schooling, and social roles compared with previous generations. Parental SES is an important influence during adolescence but cannot sufficiently capture the SES of the independent young adult. Typical, single SES indicators based on income or education likely misclassify the SES of young adults who have not yet completed their education or other training, or who have entered the labor force early with ultimately lower status attainment. We use a latent class analysis (LCA) framework to characterize five intergenerational SES groups, combining multidimensional SES information from two time points—that is, adolescent (parental) and young adult (self) SES data. Associations of these groups with obesity, a high-risk health outcome in young adults, revealed nuanced relationships not seen using traditional intergenerational SES measures. In males, for example, a middle-class upbringing in adolescence and continued material advantage into adulthood was associated with nearly as high obesity as a working poor upbringing and early, detrimental transitions. This intergenerational typology of early SES exposure facilitates understanding of SES and health during young adulthood.

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Keywords

Social class; Life course; Latent class analysis; Young adults; United States

Introduction

Chronic disease risk is influenced by exposure to social factors, such as socioeconomic status (SES), at specific points during the life span (Ben-Shlomo and Kuh 2002; Kuh et al. 2003; Lynch et al. 1997; Smith and Hart 2002). Young adulthood is a particularly susceptible period of health risks, such as obesity (Harris et al. 2006). However, given that SES exposures over time are highly correlated, disentangling the influence of earlier versus later SES on adult disease can be challenging (Hallqvist et al. 2004), especially in the context of young adulthood.

Most studies use parental SES as a proxy for SES exposure in youth through early adulthood, and thus miss the nuances of intergenerational SES transmission from parent to young adult offspring. Measures that combine parental SES in adolescence with the SES that the respondents define for themselves as young adults can capture variations in SES exposure of critical importance for adult health. The traditional approach to combining SES information uses the social mobility model (Rosvall et al. 2006), defining groups by their change in SES over time (Hart et al. 1998b). However, because social mobility studies are usually limited to single SES indicators (e.g., income or education) at two time points, groups tend to share the same SES at one of those points, which may explain the frequently observed null associations (Pollitt et al. 2005). Furthermore, single indicators likely misclassify true SES during the young adult period given the complexity, variability, and delay of the transition to adulthood in the United States today (Rindfuss 1991; Shanahan et al. 2004). Thus, a new method is needed to capture persisting parental SES effects and the influence of newly developed SES on health in young adults.

Latent class analysis (LCA) provides a novel approach to characterize intergenerational SES exposure in young adulthood. We use this model-based, probabilistic technique to discover mutually exclusive and exhaustive “classes” or groups of individuals based on their values for a large set of indicators of parental SES in adolescence and the SES that the young adults define for themselves five years later, capturing the multidimensionality of SES and more fully characterizing SES exposure over two time points during the transition to adulthood. LCA has been used in the social science literature to typify complex exposures, such as migration patterns (Burholt 1999), transitions in social roles (Moors 2008), and formation of romantic relationships (Crissey 2005), as well as labor force entry and exit (Clogg 1980). Recent work uses LCA to demonstrate the variability and complexity of transitional pathways in contemporary U.S. cohorts of young adults (Osgood et al. 2004), underscoring the need to examine parent-offspring SES groupings in a similarly multidimensional manner.

Conceptual Framework

SES is a complex attribute reflecting resources and “social position,” comprising hierarchical (“status”: i.e., the relative position or rank within an economic, a political, or a prestige hierarchy) and nonhierarchical (i.e., membership and socially defined function in an organized group) components (Benoit-Smullyan 1944). We posit that the nonhierarchical aspects of “social position” are likely to play an important role during the transition to adulthood, when hierarchical ranks are in flux, thus supporting the importance of identifying social groups of varying status configurations. Although data limitations often restrict researchers to one or two measures (Krieger et al. 1997; Oakes and Rossi 2003; Sobal and

Stunkard 1989), many consider SES to be a multidimensional construct, comprising three major domains: (1) material capital (i.e., material endowments), (2) human capital (i.e., skills and knowledge), and (3) social capital (i.e., the status, power, and resources [Moore et al. 2009] to which individuals have access through the trust, cooperation, and reciprocity of social connections [Holtgrave and Crosby 2006; Kawachi et al. 2004; Oakes and Rossi 2003; Putnam 2000]).

The literature on status attainment—that is, the processes through which initial social position is associated with status attainment over time (Schoon 2008)—provides a helpful context for defining intergenerational SES. The seminal study by Blau and Duncan (1967) showed that achieved status (i.e., status achieved at the moment of examination) was the most important determinant of ultimate attained status (i.e., status achieved at the completion of all training and transitions), even after accounting for direct and indirect effects of ascribed parental status. This work has evolved into the "Wisconsin model" (e.g., Featherman and Hauser 1978; Sewell and Hauser 1975) and continues to be reexamined in societies whose structures have changed considerably since the 1960s.

Given our interest in intergenerational SES transmission from parents to offspring, we view status attainment as a social-psychological process by which a person's family and other ascriptive characteristics influence status achievement, which is eventually translated into final status attainment (Schoon 2008). Because most young adults have not yet reached their final status, the endpoint of our intergenerational measure is limited to their temporary status achievement in young adulthood. However, our measure provides important insight on the process of attaining status by characterizing the various status configurations manifested in groups of people with different SES exposures in adolescence and young adulthood, thus enhancing the literature on intergenerational status (in)consistency (House and Harkins 1975; Kalleberg 1988; Wright 1979).

The proper conceptualization of intergenerational SES in young adults is critical to understanding how SES exposures relate to young adult health outcomes. According to cumulative frameworks of SES and health, negative SES experiences accumulate over time to influence adult disease risk (Carson et al. 2007; Hart et al. 1998a; Singh-Manoux et al. 2004). However, cumulative indices of SES are limited by their assumption that specific negative life experiences have the same impact, regardless of type or when they occur (Hallqvist et al. 2004; Pollitt et al. 2005). In this article, we use LCA to define cumulative profiles of intergenerational SES exposure in a nationally representative sample of adolescents followed into young adulthood using data from two time points, providing an innovative, alternative approach to exploring cumulative SES hypotheses. We then examine the utility of these intergenerational SES profiles in the study of SES effects on obesity in young adults.

We chose obesity as an outcome because of the high risk for obesity development during this transitional period (Gordon-Larsen et al. 2004; McTigue et al. 2002; Ogden et al. 2006), and because obesity can influence later health outcomes. Furthermore, plausible mechanisms have been posited between the three domains of SES (material, human, and social capital) and obesity through intermediate health behaviors. Material capital provides access to a variety of food and voluntary energy-expenditure opportunities, good housing, health care, and education. Human capital provides intellectual capacity for allocating resources between food and other household needs and for acquiring knowledge about the benefits of healthy eating and regular exercise (Sobal 1991). In addition, there is a nascent literature suggesting an inverse relationship between weight status and indicators of social capital (Holtgrave and Crosby 2006; Kim et al. 2006) through the diffusion of knowledge about healthy food consumption and exercise; maintenance of healthy weight-related behavioral norms; and greater access to healthcare, health education, and other local services due to a greater number and diversity of ties in cohesive areas (Kawachi and Berkman 2001).

To our knowledge, LCA has not been used to characterize intergenerational profiles of SES exposure in a young adult population, nor has it been used to understand the associations between SES and health. LCA may be useful for defining other complex exposures; furthermore, while we focus on obesity, our approach may be useful for the prediction of other behavioral and biological outcomes during young adulthood.

Methods

Latent Class Analysis (LCA)

LCA was used to identify (1) the optimal number of latent classes or groups necessary to capture heterogeneity across young adult respondents in their values on indicators of parental and young adult SES, and (2) the size and characteristics of each group. These analyses were conducted using Mplus Version 4.0, estimating parameters using maximum likelihood methods and accounting for complex survey design using a sandwich estimator for the clustering of respondents and post-stratification sample weights for the unequal probability of selection of respondents into the sample (Goodman 1974; Muthen and Muthen 1998–2006).

LCA has a distinct empirical advantage over alternative grouping methods by providing various model-fit diagnostics to determine the optimal group parameters (e.g., size and variable means) for the data. In addition, the Mplus software for LCA features full information maximum likelihood (FIML) estimation to estimate model parameters using all available data points, even for cases with missing responses. This superior method of handling missing data assumes that data are missing at random (MAR); moreover, FIML estimation methods can reduce bias even if the MAR condition is not completely satisfied (Arbuckle 1996; Muthen and Muthen 1998–2006; Wothke 2000), permitting the retention of more observations than traditional missing data methods. Furthermore, the LCA model is relatively flexible in the number and types of variables that can be included, as described below. LCA is thus well-suited to empirically conceptualize SES.

The latent class model is nonparametric and assumes that relationships among a set of observed variables are explained by an unmeasured "latent" categorical variable with discrete classes (Lazarsfeld and Henry 1968; McCutcheon 1987). In addition, the observed variables are assumed to be "locally independent" within each class defined by the latent variable; that is, members of the same group cannot be distinguished from each other and are thus homogenous with respect to these variables (Clogg 1995; Hagenaars and McCutcheon 2002). The latent class model can be used to cluster observations into groups that are similar on a set of characteristics, where the number and properties (e.g., group-specific means, variances) of the groups are unknown *a priori* (Everitt 1993; Kaufman and Rousseeuw 1990). LCA has thus become popular as a clustering technique (Vermunt and Magidson 2000), as in the present study.

Traditional LCA analyzes relationships among categorical manifest indicators, assuming a (restricted) joint multinomial distribution within class. However, LCA has recently been extended to allow manifest variables of mixed scale types (e.g., continuous, ordinal, nominal, and/or count indicators) in the same analysis (Kaplan 2004; Uebersax 2001–2003), providing another distinct advantage to this method. In this mixed mode approach, the likelihood function under the assumption of independence within a latent class is specified using the product of the univariate distributions of each manifest variable: for example, normal distributions for continuous manifest variables, (restricted) multinomial for nominal and ordinal variables, and Poisson/binomial for count variables (Hagenaars and McCutcheon 2002; Jorgensen and Hunt 1996; Vermunt and Magidson 2000). The mixed indicator specification of this model is summarized in the following equation (Hagenaars and McCutcheon 2002; Nylund 2007a):

$$f(\mathrm{y}_i)=\sum_k p\,(c=k)\ \Pi_j\ f(y_{ij}|c=k),$$

where $\mathbf{y}_i$ is the vector of observed variables for individual i, c is the discrete latent variable (k denotes a class: i.e., $k = 1, 2, \ldots K$), and $f(y_{ij}|c = k)$ is the univariate distribution specified for each y_{ij} given latent class $c = k$ (j denotes a particular indicator; i.e.,$j = 1,2,\ldots J$).

The model estimates two types of parameters: (1) latent class membership probabilities—that is, the probability of a given observation being in a particular class; and (2) conditional response probabilities—that is, the probability of a particular response pattern given membership in a particular class (McCutcheon 1987; Uebersax 2001–2003). In this study, the latent class membership probabilities summarized the distribution of respondents across the categories of the discrete latent variable representing "intergenerational SES." The conditional response probabilities described the patterns of responses to the observed SES variables for each latent class, facilitating interpretation of their salient characteristics.

Several criteria can be used to select the final latent class model. Although deciding on the number of classes is of primary interest, the typical likelihood ratio test for comparing models is not appropriate for mixture models of different numbers of classes due to the violation of regularity conditions required for asymptotic results to hold, given that some parameters are restricted to 0/1 boundary values (Everitt 1988; Lin and Dayton 1997; McLachlan and Peel 2000; Nylund 2007a). Alternative model selection criteria are available, including the following: (1) the visual plot of log-likelihoods of similarly specified models across numbers of classes to select models where the log-likelihoods "level off"—that is, no longer show a substantial improvement in model fit (Nylund 2007a); (2) the Bayesian Information Criterion (BIC), a widely used goodness of fit criterion for comparing models regardless of their underlying distribution, with smaller values representing more parsimonious models (Schwartz 1978); and (3) interpretability of model solution parameters, with specific attention to the meaningful interpretation of the pattern of response probabilities for each class, uniqueness of classes, and nontriviality of class size. After promising candidate solutions are identified, their stability can be examined by using a large number of randomly perturbed sets of starting values for the maximum likelihood estimation of model parameters. Obtaining the same model estimates across multiple sets of starting values confirms the identifiability of the model and reduces the possibility of reaching local rather than global maximum likelihood estimates (Uebersax 2001–2003).

In our study, we used the above-mentioned criteria to select a final, stable LCA model, from which we identified classes representing groups of young adults sharing a common profile of parental and young adult SES characteristics or "intergenerational SES exposure." For ease of presentation, these groups were assigned brief labels based on distinguishing characteristics. Although group comparisons were primarily qualitative, we used *post hoc* significance tests—independent *t* tests of differences in characteristics across each possible pairing of groups—as a secondary approach to comparisons. As a caveat, these tests could only be performed outside of the latent model, with the tenuous assumption of fixed (versus probabilistic) group membership.

The latent class model computes the posterior probability of an individual's membership in each class, and the individual is traditionally assigned to the group for which they have the highest probability (i.e., modal assignment) (McCutcheon 1987; Uebersax 2001–2003). In this study, for simplicity of presentation, we used modal assignments to describe the subjects most likely to be in each of these groups. However, because we exported the final latent class membership data to a nonlatent variable framework for subsequent analysis of the association between the intergenerational SES groups and obesity, we used the posterior probabilities rather than modal assignment to partially account for the measurement error of the latent classification variable. To incorporate the accuracy of class assignment into the regression analysis, the average log-odds of obesity for each SES group (regression coefficients) were weighted by the accuracy of classification (posterior probabilities of group membership) (Kleinbaum et al. 1998; Pastor et al. 2006; Rosner 2000). The weighted categories of a nominal group membership variable were then used in the prediction of young adult obesity, as described with greater detail in the regression modeling section.

Study Population and Design

We used data from the National Longitudinal Study of Adolescent Health (Add Health), a nationally representative study of health behaviors in school-aged youth (Wave I; 1994–1995; N = 20,745), followed with multiple interview waves into young adulthood (Wave III; 2001–2002; N = 15,170). Add Health is representative of U.S. students in grades 7 through 12 in 1994–1995 with respect to region of country, urbanicity, school size, school type, and race/ethnicity. This school-based study used a multistage, cluster sampling design, supplemented with special minority samples and collected under protocols approved by the Institutional Review Board of the University of North Carolina, as described elsewhere (Harris et al. 2009). Our analytic sample was drawn from the Wave III probability sample—that is, respondents interviewed in both Wave I and Wave III and who had post-stratification, longitudinal sample weights (N = 14,322). The in-home, in-school, and parental questionnaires from Wave I were used to characterize the adolescent household. The in-home questionnaire from Wave III was used to summarize the young adult experience. We excluded seriously disabled or pregnant respondents at either survey period. Although many respondents were missing data on one or more of the large set of variables (see the section SES Variables for Latent Class Analysis [LCA]) used to define our intergenerational SES exposure using LCA, the FIML estimation methods permitted the retention of all observations with any SES data, preserving overall sample size in this phase of the analysis. However, the listwise deletion of observations missing data on any covariate or outcome variables in the subsequent regression modeling reduced the dataset. Our final analytic sample included 13,432 respondents (94% of the 14,322 Wave III probability sample; 48% female) interviewed in Waves I and III, comprising four major racial/ethnic groups: non-Hispanic whites, non-Hispanic blacks, Hispanics, and Asians (98.6%, 97.8%, 75.9%, and 52.4% U.S.-born, respectively), aged 18 to 28 years at Wave III. The excluded sample had a higher proportion of females and higher young adult obesity prevalence relative to the analysis sample.

SES Variables for Latent Class Analysis (LCA)

Our desire to capture the inherent multidimensionality of the SES construct and the heterogeneity of combinations of adolescent and adulthood SES characteristics with as many variables as possible was balanced by practical limitations of the latent class model. Albeit far more flexible than traditional grouping methods, LCA, as a type of mixture modeling, can have difficulty converging as the number of variables increases, likely due to under-identification of the model (Desantis et al. 2007; Lanza et al. 2007). Currently, there are no widely accepted rules about the number of items in LCA, but most applied, published research using this technique has been performed on 30 variables or less. Starting with a large set of indicators (~50) of parental and young adult material, human, and social capital (Krieger et al. 1997; Oakes and Rossi 2003) with potential to influence weight status through intermediate behavioral factors, we iteratively eliminated or combined redundant variables to reach a final set of 25 SES indicators (toward the high end of the published range but consistent with the complexity of the measure), as listed in Table 7 in the appendix and detailed in the following sections.

Parental SES—Eleven indicators of parental SES (three continuous, six binary categorical, and two nominal categorical variables) were generated by using information from surveys of parents and adolescents from Wave I (Table 7). The "hours worked per week" variables served as indicators of degree of employment for resident parents only; nonresident parents were assigned a value of 0 because their SES was not likely to materially or socially contribute to the adolescent's household SES exposure. These variables were also an indirect confirmation of family structure. The "public assistance" indicator represented having none versus one or more sources of government assistance (including Supplemental Security Income [SSI], Aid to Families with Dependent Children [AFDC], food stamps, unemployment insurance, workers compensation, or housing subsidy) received by the parent respondent in the past month. The "social capital" indicator was a proxy for the participation dimension of Putnam's conceptualization of this SES domain (Putnam 2000), as captured in the membership of the parents in none versus one or more various formal or informal community organizations (including parent-teacher organizations, veteran's organizations, hobby or sports groups, or civic or social organizations). We also included a dichotomous indicator of family structure (i.e., "two parent household") as an integral determinant of household resources (material capital) and support (social capital) (Snyder and McLaughlin 2004; Teachman et al. 2000; Thomson et al. 1994).

Young Adult SES—Fourteen indicators of young adult SES (two continuous, 11 binary categorical, and one nominal categorical) were defined using information from the Wave III questionnaire (Table 7). We used a broad selection of variables, including enrollment in higher education, as well as measures reflecting transitions in social roles, residence, employment, and financial independence. Young adult "hardship" was defined as receipt of none versus one or more forms of public assistance (e.g., food stamps or unemployment benefits) and the experience of none versus one or more various types of hardship (e.g., inability to pay rent or inability to afford doctor visits) during the past year. Similar to the parent measure but with a greater representation of volunteer organizations, young adult "social capital" was defined by formal and informal participation in none versus one or more community organizations or activities, including youth organizations (e.g., Little League), service organizations (e.g., Big Brother/Sister), and ethnic-support groups (e.g., NAACP); as well as civic activities, including writing to a government official about political or community issues or attending a political rally.

Other Variables

Young adult obesity was defined as BMI≥30 kg/m^2 (NHLBI 1998), based on measured height and weight from Wave III, substituting self-reported height and weight values when measured values were missing (n = 330), including respondents in the analytic sample weighing in excess of scale capacity (330 lb, or 150 kg; n = 33) at Wave III. The Add Health self-report values correctly classify a large proportion of the sample (Goodman et al. 2000). Self-designated race/ethnicity from Wave I was used to create mutually exclusive categories of Hispanic, non-Hispanic white, non-Hispanic black, and Asian or Pacific Islander (for simplicity, Hispanic, white, black, and Asian). Native American respondents were excluded owing to small sample size. Gender was self-reported at Wave III, and age was reported as of the participant's last birthday at Wave III.

Regression Modeling of the Association Between Intergenerational SES and Young Adult Obesity

Poisson regression models with a robust error variance were used to estimate the relative risk of young adult obesity associated with LCA-defined intergenerational SES group membership using Stata, version 9.2 (StataCorp 2007). This “modified Poisson regression approach” (Zou 2004) directly estimates the relative risk of binary outcomes with consistency and efficiency, regardless of prevalence, and is thus particularly useful for the study of obesity in this population (~23% prevalence), given that the logistic regression approximation to relative risk is only appropriate for rare outcomes (<10% prevalence) (Greenland 2004; Lumley et al. 2006; McNutt et al. 2003). Posterior probabilities of membership in each latent class weighted the average log-odds of obesity for each SES group as the categories of a nominal predictor variable, omitting the most advantaged group (referent). Effect estimates reflect the risk of obesity associated with membership in a particular SES group relative to the referent.

Given gender differences in obesity and in the influence of SES on obesity, all models were gender stratified. Within gender, we assessed potential effect modification of the association between each SES group and obesity by race/ethnicity. Significant interactions ($p < .10$ for Wald test of interaction terms) between race/ethnicity and SES group membership were observed only in females and used to calculate racial-/ethnic-stratified estimates of the relative risk of young adult obesity, while estimates for males were pooled across racial/ethnic groups. Given the substantial proportion of foreign-born Hispanics and Asians, the significant association of foreign-born nativity with lower obesity prevalence in females and notable strengthening of associations among females with the inclusion of nativity as a covariate in preliminary modeling (data not shown), we controlled for nativity in all models.

We found borderline ($p = .15$ for Wald test of interaction terms) evidence for interaction with age among females. Preliminary models revealed stronger (more positive) associations in older females, particularly for the advantaged LCA groups. However, given the weak statistical evidence for age differences, we explored the potential for confounding by age, and although the exclusion of age did not dramatically influence the effect estimates for SES group membership, the literature and the nature of the research questions justified our control for this covariate.

We then used the Poisson model coefficients to predict adjusted obesity prevalence for each intergenerational SES category, setting other SES groups equal to 0 and age equal to the sample mean (~22 years). The probability of being in a particular race/ethnicity was set to the sample mean for predictions in males, whereas in females (data not shown), predictions were done individually by race/ethnicity, setting the other race/ethnicities (and their interaction terms) to 0. Survey procedures in Stata were used to correct for unequal probability of selection, underestimation of variance due to the clustered sample design, and nonresponse bias due to attrition from Wave I to Wave III.

Results

Descriptive Statistics

The mean age of respondents was 22, with a range of 18–28 years (Table 1). Prevalent obesity in our young adult sample was high, especially among black and Hispanic females.

Latent Class Analysis

We tested a series of models specifying between one and seven classes (Table 2). The BIC values decreased with increasing class numbers but leveled off between the four- and six-class solution, suggesting a range of acceptable class enumerations. Despite the use of a large number of randomly perturbed sets of starting values for each model specification, classes of relatively trivial size (<0.5% of the sample) and extreme values were observed for the six-class and higher solutions. Further examination of model parameters, including the values of the LCA variables across classes, provided substantive support for the five-class solution. The average posterior probability of being in a particular class for all the individuals that were assigned to that class ranged between 0.90 and 0.95 across classes for this model solution, indicating good prediction of class membership. Together, these results recommended the five-class LCA model.

Conditional response probabilities (categorical indicators) and means (continuous indicators) characterize the intergenerational SES exposure for young adults in the five latent classes identified by the model (Table 3). We refer here to LCA “groups” rather than “classes” to avoid confusion with “social class.” The Persistent Disadvantage group was characterized by an adolescent household with low parental income and likely headed by a single mother working considerably less than full time. Neither parent was likely to have more than a high school education or to have a professional occupation, and these households were least likely to have health insurance and most likely to have received public assistance. As young adults, respondents in this group reported the lowest income and years of education and were least likely to be in the labor force, but had among the highest rates of enrollment in vocational school. Furthermore, these young adults had low financial independence and the lowest rates of health insurance and social capital of any group.

The Disadvantaged Fast Starters group was characterized by adolescent households of below-average income, despite the presence of two working parents. Although the low likelihood of a professional occupation for these parents was similar to that seen for Persistent Disadvantage, they had considerably lower probability of having at least a high school education. The SES of these respondents as young adults was more complex. Although they had the second-lowest average years of education, they were less likely to be unemployed and had the second-highest income. However, they were most likely to be earning that income in a manual occupation. Although the probability of homeownership was low overall for young adults, members of this LCA group were the most likely to own their own homes and had the highest probability of being married.

Respondents in Material Advantage were exposed to a more favorable SES pattern during adolescence, characterized by the second-highest average household income and two working parents. Parental education and occupation status were relatively low, but these respondents' parents did not suffer serious hardship and had average social capital. As young adults, members of this group had the highest values for personal income and were least likely to be unemployed even though they only had average years of education and occupation status. They were nearly as likely to be in vocational school as members of Persistent Disadvantage, but they also had a nontrivial probability of enrollment in higher education.

In the Educational Advantage group, adolescence was typified by middle-income households headed by a single mother with at least a high school education and a sizable probability of having attended some college. Notably, as young adults, this group had the second-highest years of education and probability of being enrolled in higher education. This group was among the least likely to be unemployed or in manual occupations and the most likely to be working in sales or service. Although they tended to have average values for the remaining SES indicators, these young adults and their parents also had the second-highest probability of high social capital compared with other groups.

Membership in Highest Overall Advantage clearly conferred the most privileged intergenerational SES exposure. These adolescent households had the highest income of all groups and were headed by two parents with the highest probability of having professional occupations. This parental background was further characterized by the highest rates of health insurance and the lowest rates of public assistance. Similarly, respondents had the highest years of education and probability of being in higher education as young adults. Although they were less likely to be in the labor force relative to the other advantaged groups, those who were working were likely to be in managerial occupations. These respondents did not have the highest personal income in young adulthood, but they had the highest probability of having financial access and health insurance. The parents of these respondents and the respondents themselves as young adults had the highest social capital of any group.

Disadvantaged groups tended to be older, but intra- and inter-group differences were minimal (Table 4). Whites were most highly represented in the Material Advantage and Highest Overall Advantage LCA groups. Conversely, blacks were most represented in Persistent Disadvantage, with sizable representation in Educational Advantage. Hispanics were overwhelmingly represented in the Disadvantaged Fast Starters LCA group. Asians were most highly represented in the Highest Overall Advantage group.

In Table 5, as a comparative example, we show cross-classification of LCA groups with those derived from a traditional social mobility measure, using income and education at each time point (Wave I: parental SES; Wave III: young adult SES; see Table 7 for variable information) standardized to a mean of 0 and standard deviation of 1, permitting the combination of variables of different units and summarizing position relative to the population. SES at each time point was defined as the row mean of nonmissing, standardized income and education variables, dichotomized at the sample median into low versus high and used to define an *ad hoc*, four-category SES mobility variable: Stable Low = low parental SES to low young adult SES; Upwardly Mobile = low to high; Downwardly Mobile = high to low; and Stable High = high to high. Although most respondents classified as Stable Low or Stable High were captured in the least- or most-advantaged LCA groups, respectively, sizable proportions were also observed off the diagonal, in LCA groups of intermediate advantage. Also of note, the Downwardly Mobile group was most represented in the Highest Advantage LCA group. The heterogeneity of intergenerational SES patterning within each traditional social mobility group highlights the limitations of characterizing this exposure using less-dimensional methods.

Associations with Young Adult Health: The Example of Obesity

Among males, we observed approximately 50% greater risk of young adult obesity for Disadvantaged Fast Starters, Material Advantage, and Educational Advantage relative to the Highest Overall Advantage referent (Table 6). We observed strong positive associations in white females for all LCA groups relative to Highest Overall Advantage. Among black females, Disadvantaged Fast Starters was the only LCA group with significantly higher risk of young adult obesity. Hispanic females from Persistent Disadvantage were nearly three times more likely to be obese in young adulthood than Highest Overall Advantage. However, these estimates showed considerable imprecision, a problem of even greater magnitude for Asian females.

In Fig. 1, we illustrate the probability of obesity in males for each LCA group using coefficients from the Poisson models to predict young adult obesity prevalence, setting other

SES groups equal to 0 and the age equal to the sample mean (~22 years). For comparative purposes, we show predictions using the social mobility measure described in Table 5. In Fig. 1, left panel, we observe substantial differences in predicted obesity for Disadvantaged Fast Starters (highest obesity) versus Highest Overall Advantage (lowest obesity). Disadvantaged males from a single mother household (Persistent Disadvantage) had considerably *lower* risk of obesity than those from a more advantaged single mother household (Educational Advantage). In contrast, results using the social mobility model (Fig. 1, right panel) show minimal differences.

Discussion

We used a novel, LCA approach to characterize intergenerational profiles of SES exposure, combining multidimensional parental SES data from adolescence with young adult SES data. Although fairly common in the classification of complex behaviors, such as migration and labor force activities (Burholt 1999; Clogg 1980), the latent variable approach has not yet gained popularity in the study of intergenerational SES and health, despite indications that multidimensional methods could improve our understanding of these complex relationships. Associations with obesity, an important health outcome of increased risk during the young adult period, demonstrated nuanced relationships heretofore unseen using traditional social mobility measures of intergenerational SES.

Composition of Intergenerational SES Groups

Family Structure—We identified two distinct groups characterized by a single-mother household in adolescence: Persistent Disadvantage and Educational Advantage. Low-SES single mothers who transmit poverty to their offspring, as observed in Persistent Disadvantage, are a population segment that has been the focus of research and target of welfare policies in the United States for decades (McLanahan 1985, 2004). However, the highly educated single mothers of the Educational Advantage LCA group represent a relatively understudied population, which is an intergenerational SES exposure pattern not likely to be detected using traditional methods. Although only 20% of single mothers in the United States have at least some college education, the scant literature on this group suggests that these women have better social and economic family resources compared with single mothers with less education (Usdansky and McLanahan 2003; Zhan and Pandey 2004). These resources may contribute to the high likelihood of additional schooling for offspring of highly educated single mothers in this LCA group, in contrast with the lower academic achievement often observed in single-parent households (McLanahan 1985; Sandefur et al. 1992).

Profiles of Disadvantage—Differences between the two disadvantaged groups identified by LCA—Persistent Disadvantage and Disadvantaged Fast Starters—would likely be missed when using a traditional mobility approach. Members of Persistent Disadvantage were from poor households with high unemployment and hardship in adolescence, and the cycle of disadvantage continued with low education and high unemployment as young adults. In contrast, the Disadvantaged Fast Starters came from working-poor households in adolescence, but as young adults, they were more likely to be earning an income in the labor force, albeit in low-status occupations. The transitional patterns of this latter group seems most akin to the “fast starters” identified by Osgood et al. (2004), experiencing early transitions in residence, employment, and social roles to the detriment of further education.

Profiles of Advantage—The three distinct advantaged intergenerational SES groups had considerable heterogeneity. Although Highest Overall Advantage members were clearly the most well-off on a number of SES characteristics, they did not have the highest incomes in young adulthood, which could result in misclassification as Downwardly Mobile when traditional methods are used. Members of Material Advantage had a more mixed, yet still relatively advantaged SES profile; although they had the highest incomes as young adults, neither they nor their parents achieved particularly high education. Similarly, the Educational Advantage class, with its combination of a single-mother adolescent household and high academic achievement in young adulthood, would not be adequately captured by a traditional classification.

Profile Demographics—The distribution of racial/ethnic groups across disadvantaged profiles highlights the utility of LCA to define intergenerational SES. For instance, LCA demonstrates different experiences of disadvantage for blacks versus Hispanics. Blacks were more represented in the group from poor, unemployed, single-mother households (Persistent Disadvantage), consistent with research showing that blacks are more likely than whites to come from single-mother households (Bumpass and McLanahan 1989) with low income (Zhan and Pandey 2004). In contrast, Hispanics were most represented in the group from working-poor, two-parent households (Disadvantaged Fast Starters), which is supported by nationally representative data showing that a large proportion of Hispanics in the United States are underemployed (Jensen and Slack 2003; Slack and Jensen 2002), the majority of whom are "working poor" (De Jong and Madamba 2001). In addition, we found that the majority of low-SES Asians were from the working-poor, two-parent adolescent households characterizing Disadvantaged Fast Starters, which is consistent with literature on the employment and family structure of Asian families in the United States (De Jong and Madamba 2001; McLoyd et al. 2000).

The distributions of racial/ethnic groups across advantaged LCA profiles were also revealing. We found that advantaged white and Asian respondents were heterogeneous, split across the Material Advantage and Highest Overall Advantage groups. The sizable representation of blacks in the Educational Advantage group is informative although not surprising. The single-mother household for adolescents in this LCA group has become the most common family structure among black children (Kreider and Fields 2005). Furthermore, the high educational trajectories observed for young adults in this LCA group are consistent with literature showing that the typically negative impact of single-parent households on school achievement (Sandefur et al. 1992) is buffered in black adolescents by social and community support (Heard 2007).

Marriage rates in the Disadvantaged Fast Starters group (like Osgood's fast starters [2004]) were much higher than in other LCA groups. In contrast, living with parents did not distinguish classes as clearly as expected, suggesting that this may be normative for young adults in the United States today, albeit with substantial race/ethnicity heterogeneity (Iacovou 2002; Messineo 2005). However, different mechanisms may be driving similar rates of living at home (~40%) across LCA groups. For example, the unemployed, low-educated young adults in Persistent Disadvantage may be unable to support their own independent residence, whereas despite having a spouse and other pressures to live independently, the Disadvantaged Fast Starters may provide critical financial support to their impoverished parental household. On the other end of the scale, the return of college graduates to the comfort of the parental home before launching into full independence may be driving the comparable proportions living at home seen in Highest Overall Advantage (Shanahan et al. 2004). In addition, the relatively high rates of receiving income from family for both the Educational Advantage and Highest Overall Advantage LCA groups are consistent with recent research on parental outlays, showing that parents with the highest education and financial means are most likely to provide financial support to their children (Goldscheider et al. 2001; Schoeni and Ross 2004).

Associations with Obesity

Obesity has reached epidemic proportions in the United States, although not all groups are affected equally. There is clear need for methods (such as LCA) to better understand the complex and heterogeneous SES patterning that may predispose risk. In general, we find more-nuanced associations with obesity using LCA than simpler approaches. Among males, the highest risk of obesity was observed in two very distinct profiles of SES exposure—Disadvantaged Fast Starters and Material Advantage—while Persistent Disadvantage was not related to obesity despite impoverished SES exposure across generations. In contrast, the strongly elevated risk of obesity observed in white females in Persistent Disadvantage suggests that characteristics of this LCA group can be particularly harmful for some segments of the population.

The null association of the Persistent Disadvantage group in black females is surprising, given that the cumulative burden hypothesis, often invoked in the study of SES and health in blacks (Baltrus et al. 2005; James et al. 2006), would predict particularly strong effects for this intergenerational SES profile. This finding may suggest resilience to the health effects of persistent poverty among blacks due to the history of low SES through multiple generations. Disadvantaged Fast Starters, however, reflect a historically recent profile of adverse SES exposure among blacks, which may explain why this profile retains demonstrable (albeit marginal) health effects in this racial/ethnic group. Perhaps Hispanics show expected results because their status in U.S. society resembles that of blacks from several generations ago: that is, the persistence of low SES from parent to child may still be a powerful predictor of poor health in Hispanics, whereas this status has become normative (and less influential for health) among U.S. blacks.

These racial/ethnic-specific findings in females are also noteworthy for their contrast to the results in males, which did not differ by race/ethnicity, suggesting that the influence of a well-characterized socioeconomic exposure on obesity may override racial/ethnic distinctions in obesity risk for males. Given the extraordinarily adverse SES profile in young adulthood (presumably associated with *higher* obesity risk) for the Persistent Disadvantage group, the surprisingly lower risk of obesity among males in this group is likely attributable to something about parental SES in adolescence that protects males but not females. We may speculate that daughters are more likely than sons to adopt improper weight-loss behaviors from their impoverished single mothers.

Implications for Conceptual Models of Intergenerational SES and Health

LCA provided an alternative and perhaps enhanced approach to defining intergenerational SES, permitting classification based on a multidimensional set of SES characteristics across generations and capturing heterogeneity in the cumulative SES experience of young adults. Indeed, the heterogeneous distribution of respondents classified by the LCA categories in contrast with those derived from the less-complex traditional social mobility categories highlights the limitations of characterizing intergenerational SES exposure with simple SES classification schemes. Furthermore, our interaction approach to exploring the influence of SES and race/ethnicity on health permitted focus on the different profiles of SES exposure that may be more obesogenic regardless of race/ethnicity for males and by race/ethnicity for females, facilitating examination of poor health in socioeconomic terms.

Limitations and Strengths

Our work is based on the short time frame (approximately five years) between adolescence and young adulthood. Although this is a meaningful period of increased risk for obesity, it is only a brief window in the life span. Clearly, more can be gained from future work using LCA methods over longer periods of time. We are also limited in having SES data from two time points as the basis of the LCA analysis. Furthermore, while our comparison between LCA results and those from a social mobility measure demonstrates the advantages of LCA, the social mobility model is clearly most appropriate for individuals who have completed the transition from adolescence to adulthood and thus may be a "straw man." However, dramatic and complex transitions in schooling, employment, residence, and social roles during this period generate considerable variability in SES that warrant focused investigation.

In a similar vein, we acknowledge that the age range of our sample is relatively wide, from the perspective of this dynamic transitional period, and thus it is likely that older respondents had a greater opportunity to define their own SES than had younger respondents; this was apparent in the older age of mobility groups with high young adult SES (data not shown), although group differences were generally minimal. We did not expect age to be problematic for the LCA groups due to the large number and wide variety of items summarizing multiple dimensions of SES relevant to young adulthood, thus reducing the impact of age-related misclassification by any single indicator. Indeed, although the older age of the Disadvantaged Fast Starters may reflect enhanced opportunity to achieve the age-related transitional milestones that characterize this group (e.g., marriage, homeownership), the similarly older average age of the Persistent Disadvantage group does not reflect the exploitation of any obvious age-related opportunities. Furthermore, we addressed the role of age in the association between the intergenerational SES groups and obesity during the building of our multivariable Poisson regression models, ultimately retaining age as a confounder. Analysis of a sample restricted to the 5th–95th percentile of the age range produced results nearly identical to our original estimates, suggesting some degree of consistency regardless of whether we exclude the extremes of the age distribution. Moreover, given the delay and variability in the timing of the transition to adulthood in current times, the 10-year age span of our study may be uniquely suited to capture a more complete picture of the full transition period.

Given the temporality of our data, we considered a latent transition analysis (LTA), a longitudinal extension of the LCA model that characterizes how people move between classes of the same latent variable across time points (Collins et al. 2000; Lanza et al. 2003). However, the inherent complexity of the young adult period rendered the latent SES construct at Wave III incomparable to the latent measure of parental SES (Wave I), thus obviating the use of LTA to capture intergenerational SES profiles because LTA necessitates that latent variables be measured the same way over time (Nylund 2007b). Thus, given the (intentional) differences in how we defined parental versus young adult SES, LCA was a more appropriate (albeit less longitudinal) latent variable approach to define our SES groups.

In our sample, approximately 20% of the single mothers of adolescent respondents had never been married, while the majority were separated, divorced, or widowed. We were unable to distinguish these subtypes using LCA, and thus our results are comparable to many population studies, for which detailed data on marital status is unavailable. Our sample was also characterized by a high proportion of foreign-born Hispanics and Asians who were marginally more likely to be classified (1 to 2 percentage points higher) in disadvantaged LCA groups than their U.S.-born counterparts (data not shown). We controlled for nativity in associations between SES and obesity, but it would be interesting to explore the impact of more detailed heterogeneity within racial/ethnic groups in future, larger studies.

We used median splits to dichotomize the SES measures for social mobility at each time point, consistent with our standardization of these measures and desire to distinguish high and low SES relative to the population. However, this approach may misclassify SES on an absolute scale, which in turn affects our four-level social mobility grouping. As such, alternative social mobility strategies that divide the distribution at each time point based on substantive rationale may be recommended for a stricter comparison with the LCA method.

We recognize that the LCA results are contingent on the variables entered into the latent class model. However, we include a large set of parental and young adult SES indicators, covering a breadth of domains consistent with established theory on the nature of SES construct (Benoit-Smullyan 1944; Krieger et al. 1997; Oakes and Rossi 2003), with particular attention to the inclusion of appropriate SES indicators for the complex young adult period (Scharoun-Lee et al. 2009). This, in tandem with the empirical tools for selecting optimized model solutions in LCA, provides confidence in our results. Moreover, our primary intention was to explore hypotheses about the definition of SES in young adults and potential associations with health. In a similar vein, although we focus on individual-level measures of SES, we recognize that addressing community-level measures of SES is clearly an important next step that is beyond the scope of this manuscript. Study strengths include the large population size, the wide range of data on SES indicators, and the ability to make nationally representative estimates. Furthermore, in contrast with many intergenerational studies, the data were collected prospectively, minimizing potential for recall bias.

Conclusion

LCA permitted classification based on a multidimensional and intergenerational set of SES characteristics, providing a detailed picture of what defines (dis)advantage in cumulative life course SES exposure for young adults in a manner not possible using a social mobility framework. For instance, three distinct advantaged life course SES groups were revealed, demonstrating considerable heterogeneity in income, education, public assistance, social capital, health insurance, and other complex attributes. In addition, our findings suggest that groups identified by LCA provide more nuanced relationships with health outcomes than traditional intergenerational SES measures. For example, growing up in a disadvantaged household and continuing that disadvantage into adulthood was associated with substantially elevated obesity risk for white females; whereas in males, a middle-class upbringing in adolescence and continued material advantage into adulthood was associated with nearly as high obesity as a working-poor upbringing and early, detrimental transitions. This intergenerational typology of early SES exposure facilitates our understanding of SES and health during the transition to adulthood.

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Appendix

Table 7

Description of parental and young adult SES variables used to define intergenerational SES using social mobility framework and latent class analysis in longitudinal sample with weights (*N* = 14,322) from the National Longitudinal Study of Adolescent Health

Variable Name	Description	Coding	
Parental SES			
Continuous			Mean
Household income[a]	Regression imputed family income variable[d,e]	0–300, in thousands	42
Hours work/week, mother	Hours/week mother works (Wave I); 0 = no mom or no job[d]	0–70	32
Hours work/week, father	Hours/week father works (Wave I); 0 = no dad or no job[d]	0–80	30
Binary/nominal			%
Two-parent household	Two-biological-parent household[d,e]	0 = no, 1 = yes	.50
Insurance 12 mo.	Have you (parent) had health insurance last 12 months?[d]	0 = no, 1 = yes	.81
Parent public assistance[b]	Number of sources of public assistance[d]	0 = none, 1 = some	.29
Social capital[b]	Sum of total social capital variables[d]	0 = none, 1 = some	.50
Mother Professional	Is mother a professional?[d,e,f]	0 = no, 1 = yes	.24
Father Professional	Is father a professional?[d,e,f]	0 = no, 1 = yes	.24
Mother's education <high school	Mother's highest educational attainment[d,e,f]	<High school	.18
Mother's education high school graduate		High school	.57
Mother's education some college		Some college+	.25
Father's education <high school	Father's highest educational attainment[d,e,f]	<High school	.18
Father's education high school graduate		High school	.53
Father's education some college		Some college	.17
Father's education graduate/professional		Graduate/professional school	.12
Parent's education <high school[c]	Highest education of either parent, mother's education when available[d,e]	<High school	.14
Parent's education high school graduate[c]		High school/GED	.31
Parent's education some college[c]		Some college	.26
Parent's education college graduate[c]		College graduate	.15
Parent's education graduate/professional[c]		Graduate/professional school	.09
Young Adult SES			
Continuous			Mean
Personal income[a]	Young adult income using best-guess assignment when “don't know”; truncated at 99th percentile	0–300, in thousands	13.6
Years of education[a]	Highest grade/year completed (Wave III)	6 to 22	13.2
Binary/nominal			%
Ever-married	Number of marriages (Wave III)	0 = none, 1 = 1+	.19

Variable Name	Description	Coding	
Live with parent	Live with parents (Wave III)	0 = no, 1 = yes	.41
In college	Currently attending college (AA/ BA; Wave III)	0 = not 1 = in college	.36
Vocational school	Currently attending vocational school (Wave III)	0 = no, 1 = yes	.24
Savings account	Do you have a savings account (Wave III)	0 = no, 1 = yes	.64
Income from family	Do you get income from your family/friends (Wave III)	0 = no, 1 = yes	.40
Own residence	Do you own a residence (Wave III)	0 = no, 1 = yes	.12
Credit card	Do you have a credit card (Wave III)	0 = no, 1 = yes	.59
Health insurance	Do you currently have health insurance (Wave III)	0 = no, 1 = yes	.76
Hardship[b]	Number of sources of public assistance and hardship (Wave III)	0 = none, 1 = 1+	.36
Social capital[b]	Number of volunteer organizations and social capital activities (Wave III)	0 = none, 1 = 1+	.31
Job description	Young adult job description (Wave III)	Not working	.31
		Blue collar	.13
		Sales and service	.37
		Manager/professional	.19

[a]Variable used in both LCA and traditional social mobility approach to defining intergenerational SES.

[b]See the text for further details on variable composition.

[c]Variable used only traditional social mobility approach to defining intergenerational SES.

[d]Source data: Parent questionnaire.

[e]Source data: In-home questionnaire.

[f]Source data: In-school questionnaire.

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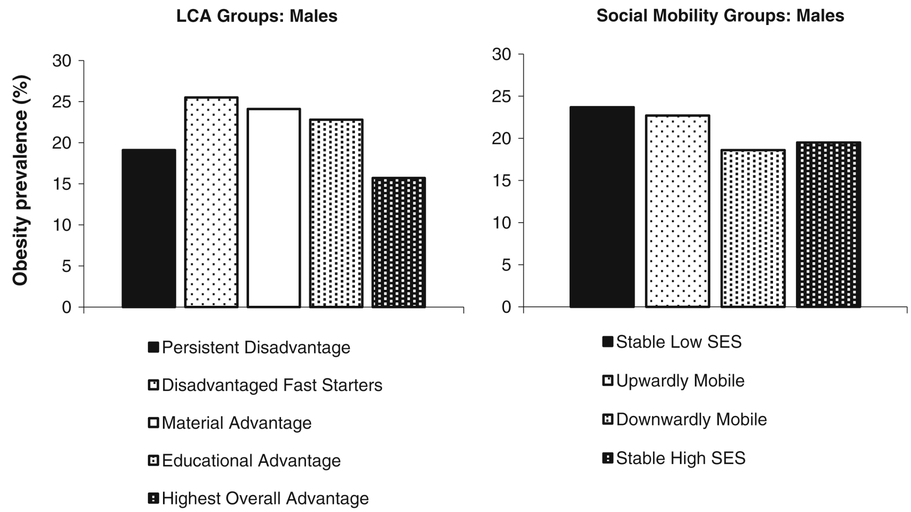

Fig. 1.
Predicted obesity prevalence for an average, 22-year-old male, pooled by race/ethnicity, across intergenerational SES groups (Add Health Wave III; 2000–2001).
Notes: Coefficients from Poisson regression model in males were used to predict the probability of young adult (Wave III) obesity for each intergenerational SES category, setting other SES groups equal to 0 and the age equal to the sample mean (22 years). The predictions were also pooled by race/ethnicity, setting the probability of being in a particular racial/ethnic group equal to the sample mean.

Table 1

Demographic and background data on longitudinal analysis sample (*N* = 13,432) from Wave I (1994–1995) and Wave III (2000–2001) of the National Longitudinal Study of Adolescent Health

Characteristic	Total	Males (*n* = 6,509)	Females (*n* = 6,923)
Age (Wave III) (mean)	21.8 (0.1)		
Female (%)	47.9 (0.6)		
White (%)	68.4 (2.9)		
Black (%)	15.8 (2.1)		
Hispanic (%)	11.8 (1.7)		
Asian (%)	4.0 (0.8)		
Young Adult Obesity (Wave III)	22.7 (0.8)		
White		21.0 (1.0)	21.9 (1.3)
Black		24.1 (1.7)	34.7 (2.0)
Hispanic		21.2 (1.6)	27.8 (1.9)
Asian		17.5 (3.4)	9.6 (2.5)

Notes: Weighted and corrected for clustering to generate nationally representative estimates. Numbers in parentheses are standard errors.

Table 2

Model fit for one- to seven-class specification of latent class analysis model

Number of Classes	Log-Likelihood	Number of Parameters	BIC	Change in BIC
1	−461,408	35	923,151	–
2	−448,424	66	897,479	−25,672
3	−443,729	97	888,385	−9,094
4	−438,166	128	877,556	−10,829
5	−435,678	159	872,878	−4,678
6	−433,783	190	869,385	−3,493
7	−432,225	221	866,565	−2,820

Note: BIC = Bayesian information criterion.

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Table 3

LCA group membership probabilities and conditional response probabilities for latent class analysis of intergenerational SES in the longitudinal sample with weights (*N* = 14,322) from the National Longitudinal Study of Adolescent Health

LCA Groups	Persistent Disadvantage	Disadvantaged Fast Starters	Material Advantage	Educational Advantage	Highest Overall Advantage	Total
Percentage of Sample	**18.9%** (*n* = 2,713)	**16.0%** (*n* = 2,293)	**27.3%** (*n* = 3,913)	**13.7%** (*n* = 1,962)	**24.0%** (*n* = 3,442)	**100%** (*N* = 14,322)
Conditional Response Means and Probabilities						
Parental SES						
Continuous variable means						
Income/thousands	19.7[a]	31.1[b]	43.5[c]	35.4[d]	72.8[e]	43.0
Hours work/week, mother	27.5[a]	29.0[a]	31.5[b]	36.2[c]	31.8[b]	31.3
Hours work/week, father	0.63[a]	45.2[b]	46.2[b]	0.70[a]	46.2[b]	31.1
Binary/categorical variable probabilities						
Two-parent household	0.09[a]	0.74[b]	0.75[b]	0.09[a]	0.87[c]	0.56
Insurance 12 months	0.64[a]	0.65[a]	0.86[b]	0.85[b]	0.97[c]	0.81
Public assistance	0.67[a]	0.31[b]	0.17[c]	0.27[d]	0.06[e]	0.27
Social capital	0.27[a]	0.29[a]	0.50[b]	0.61[c]	0.79[d]	0.51
Mother professional	0.09[a]	0.08[a]	0.14[b]	0.35[c]	0.49[d]	0.23
Father professional	0.07[a]	0.07[a]	0.09[b]	0.22[c]	0.53[d]	0.24
Mother's education less than high school	0.36[a]	0.58[b]	0.00[c]	0.04[d]	0.02[d]	0.17
Mother's education high school graduate	0.58[a]	0.35[b]	0.92[c]	0.66[d]	0.40[b]	0.60
Mother's education some college	0.06[a]	0.07[a]	0.08[a]	0.30[b]	0.58[c]	0.23
Father's education less than high school	0.35[a]	0.64[b]	0.00[c]	0.07[d]	0.02[e]	0.17
Father's education high school graduate	0.58[a]	0.22[b]	1.00[c]	0.61[a]	0.24[b]	0.45
Father's education some college	0.04[a]	0.10[b]	0.00[c]	0.22[d]	0.40[e]	0.55
Father's education graduate/professional	0.03[a]	0.04[a]	0.00[b]	0.10[c]	0.34[d]	0.16
Young Adult SES						
Continuous variable means						

LCA Groups	**Persistent Disadvantage**	**Disadvantaged Fast Starters**	**Material Advantage**	**Educational Advantage**	**Highest Overall Advantage**	**Total**
Percentage of Sample	**18.9% (*n* = 2,713)**	**16.0% (*n* = 2,293)**	**27.3% (*n* = 3,913)**	**13.7% (*n* = 1,962)**	**24.0% (*n* = 3,442)**	**100% (*N* = 14,322)**
Conditional Response Means and Probabilities						
Income (thousands)	11.4^{a}	13.9^{b}	14.6^{b}	13.8^{b}	13.1^{a}	13.4
Years of education	11.6^{a}	12.1^{b}	12.9^{c}	13.8^{d}	14.6^{e}	13.0
Binary/categorical variable probabilities						
No job	0.38^{a}	0.29^{b}	0.25^{b}	0.26^{b}	0.33^{a}	0.30
Manual occupation	0.19^{a}	0.23^{a}	0.20^{a}	0.07^{b}	0.05^{b}	0.15
Sales/service occupation	0.36^{a}	0.35^{a}	0.38^{a}	0.41^{b}	0.35^{a}	0.37
Managerial occupation	0.07^{a}	0.13^{b}	0.17^{b}	0.26^{c}	0.27^{c}	0.18
Ever-married	0.22^{a}	0.28^{b}	0.22^{a}	0.15^{c}	0.09^{d}	0.19
Live with parent	0.40^{a}	0.44^{a}	0.45^{a}	0.37^{b}	0.37^{b}	0.41
Income from family	0.27^{a}	0.29^{a}	0.34^{b}	0.46^{c}	0.62^{d}	0.40
In college (high ed.)	0.09^{a}	0.17^{b}	0.30^{c}	0.50^{d}	0.64^{e}	0.35
In vocational school	0.29^{a}	0.26^{a}	0.28^{a}	0.22^{b}	0.14^{c}	0.24
Savings account	0.40^{a}	0.55^{b}	0.65^{c}	0.72^{d}	0.77^{d}	0.62
Credit card	0.30^{a}	0.48^{b}	0.58^{c}	0.74^{d}	0.75^{d}	0.58
Own residence	0.13^{a}	0.17^{b}	0.16^{b}	0.12^{a}	0.08^{c}	0.13
Hardship	0.58^{a}	0.43^{b}	0.35^{c}	0.33^{c}	0.22^{d}	0.37
Health insurance	0.56^{a}	0.63^{b}	0.77^{c}	0.82^{d}	0.93^{e}	0.75
Social capital	0.15^{a}	0.20^{b}	0.24^{c}	0.40^{d}	0.50^{e}	0.30

Notes: N = 14,322 is larger than the multivariate modeling sample shown in Tables 1, 4, and 5 because maximum likelihood methods in LCA software permitted retention of full sample with weights, whereas exclusions and listwise deletion of observations with missing values reduced sample size for multivariate models. "Percentage of sample" is based on the summary of modal assignments for each subject derived from their highest posterior probability of group membership.

[a–e] In each row, values with the same alphabetic superscript are not significantly different from each other, but are significantly different from values with different superscripts ($p < .05$ with Bonferonni correction) based on post hoc *t* tests of pairwise group differences.

Table 4

Distribution of intergenerational SES groups by age and race/ethnicity in longitudinal analysis sample (*N* = 13,432) from the National Longitudinal Study of Adolescent Health

Intergenerational SES Groups	Age (years)	White (*n* = 7,370) %	Black (*n* = 2,833) %	Hispanic (*n* = 2,211) %	Asian (*n* = 1,018) %
LCA Groups					
Persistent Disadvantage	22.1 (0.16)	13.6 (1.0)	37.6 (2.5)*	22.5 (2.0)*	7.2 (1.8)*
Disadvantaged Fast Starters	22.0 (0.15)	12.9 (0.8)	10.1 (1.0)*	39.0 (3.2)*	18.7 (2.9)
Material Advantage	21.7 (0.13)	31.1 (1.3)	18.6 (1.1)*	17.0 (1.7)*	25.6 (3.2)
Educational Advantage	21.8 (0.13)	12.3 (0.4)	23.3 (1.6)*	10.4 (1.1)	13.8 (1.6)
Highest Overall Advantage	21.6 (0.14)	30.1 (2.0)	10.4 (1.7)*	11.1 (1.6)*	34.7 (3.1)
Total	21.8 (0.14)	100.0	100.0	100.0	100.0

Notes: The percentage (%) of respondents in each intergenerational SES group are presented by race/ethnicity, weighted and corrected for clustering. Numbers in parentheses are standard errors. Columns may not sum to 100.0% because of rounding.

* $p < .05$ for differences between “white” and the indicated race/ethnicity in the mean proportion of subjects in each SES group based on Student's *t* tests.

Table 5

Cross-classification of longitudinal analysis sample (*N* = 13,432) from the National Longitudinal Study of Adolescent Health into intergenerational SES groups defined using a latent class analysis versus a social mobility framework

	Social Mobility Groups[a]				
LCA Groups	**Stable Low (n = 3,741) %**	**Upwardly Mobile (n = 2,630) %**	**Downwardly Mobile (n = 2,739) %**	**Stable High (n = 4,323) %**	**Total (N = 13,432) %**
Persistent Disadvantage	40.5	17.3	10.2	2.0	18.2
Disadvantaged Fast Starters	25.9	23.1	8.8	4.6	15.3
Material Advantage	22.7	34.6	32.8	26.7	28.2
Educational Advantage	8.6	19.3	13.5	15.5	13.7
Highest Advantage	2.2	5.7	34.8	51.2	24.6
Total	100	100	100	100	100

Notes: LCA = latent class analysis. See the text for details on the definition of these groups.

[a]Social mobility groups were defined using the average standardized income and education at Wave I (parental) and Wave III (young adult). Stable Low = low parental SES to low young adult SES; Upwardly Mobile = low to high; Downwardly Mobile = high to low; and Stable High = high to high.

Table 6

The association between intergenerational SES and young adult obesity prevalence in longitudinal analysis sample (*N* = 13,432) from the National Longitudinal Study of Adolescent Health

Intergenerational SES Groups	Relative Risk (95%confidence interval)				
		Females[a]			
	Males	White	Black	Hispanic	Asian
LCA Groups					
Persistent Disadvantage	1.21 (0.95, 1.54)	2.84 (2.03, 3.95)*	1.29 (0.84, 1.99)	2.80 (1.21, 6.92)*	4.84 (0.59, 39.6)
Disadvantaged Fast Starters	1.64 (1.27, 2.13)*	2.69 (1.94, 3.73)*	1.57 (1.07, 2.36)*	1.99 (0.83, 4.76)	0.90 (0.10, 7.79)
Material Advantage	1.53 (1.24, 1.89)*	2.17 (1.59, 2.95)*	1.22 (0.78, 1.92)	2.30 (0.93, 5.68)	3.23 (0.71, 14.6)
Educational Advantage	1.46 (1.13, 1.88)*	1.66 (1.21, 2.26)*	1.24 (0.80, 1.92)	1.27 (0.47, 3.44)	4.77 (1.18, 19.2)*
Highest Overall Advantage[b]	1.00	1.00	1.00	1.00	1.00
Referent Obesity Prevalence[c]	16.2 (1.3)	12.5 (1.5)	28.5 (4.3)	14.8 (5.7)	4.0 (2.4)

[a]Significant interactions ($p < .10$) between race/ethnicity and the intergenerational SES group membership variable were observed in females and used to calculate racial-/ethnic-stratified estimates of the relative risk of young adult obesity.

[b]Poisson regression models in both males and females were used to directly estimate the relative risk of obesity in young adulthood associated with membership in the indicated intergenerational SES group versus Highest Overall Advantage (referent), adjusted for age, nativity, and race/ethnicity (males only).

[c]Obesity prevalence rates (expressed as a percentage, with standard errors in parentheses) in the referent intergenerational SES group across gender and race/ethnicity are provided for context.

*$p < .05$ for coefficient on indicated intergenerational SES group versus high SES referent group (i.e., 95% confidence interval on relative risk estimate excludes null value of 1.00)