Socioeconomic Status and Health Over the Life-Course
: An Aging-Vector Approach*

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**SOCIOECONOMIC STATUS AND HEALTH OVER THE LIFE COURSE:
AN AGING VECTOR APPROACH**

ABSTRACT

Using the ACL national probability sample collected in 1986, 1989, and 1994, this study comprehensively examines the life-course pattern in health by socioeconomic status (SES) because previous studies have provided inconsistent results about the pattern. The results utilizing aging-vector approach, an innovative growth curve modeling, suggest that the physical health gaps by education and income diverge over time in all age groups, including old ages, so cumulative advantage hypothesis is strongly supported. Education-based gap in depression also shows divergence, but income-based gap in depression shows convergence in old age, supporting age-as-level hypothesis, based on increasing maturity in older age. Trend effect relatively more favoring higher SES group (especially in younger cohorts) partially contributes to the divergence over time, supporting the hypothesis that education's effect on health is stronger in more recent period or newer cohorts. Aging-vector approach in this study provides effective understanding about life-course health inequality, based on contemporary trend.

Socioeconomic Status and Health Over the Life Course: An Aging-Vector Approach

Does the relationship between socioeconomic status (SES hereafter) and health change over the life-course? Does health diverge over time across levels of education and income for all age groups or diverge for the younger age groups but converge for the older ones? Is education becoming increasingly important to health outcomes in more recent cohorts with contributing to rising health inequality? Those are main questions which this study intends to answer. With rising attention to SES as a fundamental cause of health disparity (Link and Phelan 1995; Haan et al 1989; Williams and Collins 1995; Adler and Ostrove 1999), it is still unclear how the SES-based health inequality varies over the life-course.

Previous studies' findings, nevertheless, can be summarized two distinct patterns – one is consistent diverging gap by SES over the life course, and the other is diverging gap until early old age and convergence in later life. For the mechanisms of divergence, most of them support cumulative advantage hypothesis (Dannefer 1987; Crystal and Krishnaswami 1992; O'Rand 1995) – the divergence is explained as results from the accumulation of various resources related to SES. In cross-sectional approach, consistent divergence with age was founded in several studies about physical health by education (Ross and Wu 1996), depression by education (Miech and Shanahan 2000), and physical illness by income (Aneshensel et al 1984). In contrast, divergence to convergence pattern was also founded in several studies about physical health by education (House et al 1994; Beckett 2000), mortality by education (Elo and Preston 1996), and activity limitation by poverty (Newacheck et al 1980).

In longitudinal approach, Ross and Wu (1996) confirmed additional effect of education on health change net of health at baseline, using one year interval panel data. To the extent that the changes accumulate, the education-based gap is expected to increase more and more with age. With employing 30 years' pooled repeated survey, Lauderdale (2001) suggested the necessity to take into account cohort variations in effect of education on survival. After controlling for the cohort effect, education-based gaps on survival extended with increasing age within each cohort. In contrast, House and colleagues (1994) founded that education's effect on change of functional health is smaller in older ages than in middle ages, using 2.5 years longitudinal data. Beckett (2000) also founded same pattern in different data, even after taking into account mortality selection bias – in which the least healthy, who are disproportionately of low SES, are more likely to have died or for other reasons related to SES, to not participate in a survey. A recent study (Lynch 2003) employed growth curve modeling, which reduces mortality selection bias, to examine life-course relationship between education and self-rated health. The education-based gap diverged over survey period (about 20 years) in cohorts aged between 20 and 46 at baseline, but it converged in cohorts aged between 47 and 74 at baseline. Lynch interpreted the convergence as a consequence from that education's effect is smaller in older cohorts.

In cross-sectional analysis, age effect can not be disentangled from cohort difference (Reily 1987) – age variable represents both age aspect and cohort aspect. However, if the age aspect play a substantial role in the age interaction with SES, the results from cross-sectional studies would reflect validly the life-course health pattern by SES at large. Nevertheless, strictly speaking, cross-sectional age pattern is not about direct "aging process", so longitudinal studies need to complement cross-sectional studies. Although previous several studies employed short longitudinal data, growth curve modeling with longer period data might be more recommended because the modeling examines health trajectory within a person over substantial length of time to capture aging process and has additional advantage of reducing mortality selection bias (Lynch 2003).

An ideal method for studying life-course patterns in health would be to follow the same persons throughout their lives to examine their health trajectories. However, due to the investment of time and money required to carry out a large-scale longitudinal surveys, the availability of long-term panel data spanning the life course is extremely limited. In addition, long-term panel data often involves severe sample attrition. Finally, those data sources that follow only a few cohorts over time have an additional problem: the limitation in generalizability to other cohorts.

The present study uses the "aging-vector model", an innovative growth-curve model, to examine health trajectory over time for 1-year age groups or birth cohorts (Mirowsky and Kim 2004). The aging-vector model was recently developed as a complementary approach to study the long-term life course with relatively short-term panel data (less than 10 years). The present study demonstrates show the applicability and the strengths of the aging-vector model and the aging-vector graph in various life-course inequality research. The aging-vector approach provides a composite image of the entire life-course pattern, based on segmental aging patterns, expressed in the form of vectors, during a given survey period within a broad range of age groups at baseline. Because the effect of education appears to be stronger among more recent cohorts, investigations of the moderating effect of age in the association between education and health must take into consideration trend effects (Lauderdale 2001; Lynch 2003). The aging-vector approach allows for the comparison of cross-sectional curves and aging vectors, revealing the influence of historical trend in the life course pattern. Another advantage of this approach is that it lends itself to effective graphical presentations of results, making interpretation of complex patterns clear and relatively simple.

Using panel data (1986-1994) based on a national probability sample from the America's Changing Lives (ACL) survey, this study examines the cumulative effects of education and family income on physical and mental health across the adult life course. We expect to find divergence in health trajectories by SES across all ages, lending support to the cumulative advantage hypothesis. We also address various methodological issues inherent to the study of life course patterns and demonstrate the strengths and utility of the aging-vector approach in life course inequality research.

SES AND PHYSICAL AND MENTAL HEALTH

Numerous studies have investigated the relationship between socioeconomic status and health. Because behavioral factors proximal to health might be determined by distal SES factors, the focus of social intervention aimed at reducing inequalities in health is best placed on decreasing the gap in SES. Moreover, as a public health issue, health inequality is not solely a problem of the poor; there is a consistent relative gap (gradient) in health across all SES groups. A number of mechanisms have been suggested to explain the persistent relationship between SES and health. For example, SES affects health behaviors (such as smoking, exercise, and diet), medical care usage (accessibility of care as well as quality of care), psychosocial resources (such as the sense of control and social support), and community or residential environments (Haan et al 1989; Williams and Collins 1995; Adler and Ostrove 1999).

This study considers two dimensions of SES – education and income. Mirowsky and Ross (2003) described the critical role of education in producing health, emphasizing the benefits that accrue from the acquisition of human capital obtained through education, rather than the credential itself. Although many studies have examined the effects of education on health, recent work suggests the necessity to study other dimensions of SES, such as income and wealth, as different dimensions of SES might show different patterns in their relationship with various health outcomes (Williams and Collins 1995; Smith and Kington 1997; Benzeval and Judge 2001).

In addition to physical health measures, the present study includes depressive symptomatology as a health outcome. Considering mental health as well as physical health provides a more comprehensive understanding of the relationship between SES and health over the life course. The relationship between SES and mental health is often explained using the stress paradigm, which posits that differences in stress exposure and stress responsiveness account for SES differences in mental health (Wheaton 1978; Kessler and Cleary 1980; Pearlin 1989; Turner et al 1995). For example, lower SES individuals might be disadvantaged in psychosocial resources, so the difference in coping ability can result in the difference in psychological distress. Ross and Willigen (1997) identified several mediators including work or economic conditions (factors corresponding to stress exposure), social support, and the sense of control (factors corresponding to psychosocial resources) to explain education's effect on emotional well-being.

SES-Based Life-Course Patterns in Health

Because health outcomes in later life are related to earlier life stages, health status should be considered as a lifelong process (George 2003; Elder and Johnson 2002). Health inequality among the elderly can be viewed in part as a consequence of "lifelong differential opportunities and achievements," or a cumulative process occurring over the life course (O'Rand 1995).

Previous research on the moderating effect of age in the relationship between SES and health or mortality remains equivocal. One group of studies found an SES-based diverging gap in health outcomes with age (Aneshensel et al 1984; Ross and Wu 1996; Miech and Shanahan 2000; Lauderdale 2001), another group found convergence in health outcomes in later life (Kitagawa and Hauser 1973; House et al 1994; Elo and Preston 1996; Beckett 2000), and others found a constant gap in later life (Maddox and Clark 1992). Two contrasting hypotheses can be used to explain the first two life-course patterns, especially those observed in later life – the cumulative advantage hypothesis and the age-as-leveler hypothesis. The cumulative advantage hypothesis was originally developed to explain the diverging gap in occupational achievement observed over the professional careers of scientists (Merton 1968), and has been more recently applied to the study of health (see Ross and Wu 1996) and the life course (Dannefer 1987). For example, in their study of the effects of education on health over the life course, Ross and Wu (1996) suggested that a cumulative advantage of education exists over the life-course, generating the largest gaps in health in later life.

The shift to convergence in health in old age found in some studies is typically explained with the age-as-leveler hypothesis, which holds that the converging pattern found in later life is the result of universal biological frailty in old age and government support to the elderly, which narrows the gap in economic resources in old age. Following this hypothesis, SES differences in risk factors such as health behaviors, stress, the sense of control, and social support are small in early adulthood, greater during middle and early old age, and small again in later life. Socioeconomic disadvantages in risk factors accumulate throughout most of adulthood but diminish in later life as a result of selection, the equalization of health risks, and the narrowing gap in economic resources due to retirement and government support (Social Security and

Medicare) in later life (House et al 1994). However, Dannefer (1987) argues that the equalizing effect of social welfare is limited and does not overcome SES-based inequality among the elderly. This argument is supported by the work of Crystal and colleagues (1992), who found that the effect of education on income does not diminish among the elderly, that while Social Security income narrows the resource gap to an extent, private pensions and other sources of income were highly dependent upon educational attainment.

The World Health Organization (WHO) defines health as "a state of complete physical, mental, and social well-being…" emphasizing the multidimensional nature of health. Previous studies investigating SES and health over the life course have primarily focused on physical health; thus we know little about the effects of SES on mental health over the life course. The life-course pattern between SES and mental health should be examined in order to understand potential variations in health inequality by various health outcomes. Although several studies in the stress paradigm explain the SES-based gap in mental health with differences in stressful life events (Turner et al 1995), only a few studies have examined the life-course pattern (i.e., an age interaction) between SES and mental health as their primary research topic (Miech and Shanahan 2000; Schieman 2001). Using cross-sectional data, Miech and Shanahan's study (2000) found an education-based consistent diverging gap in depression over the life course, and Schieman's (2001) study also found a cumulative advantage of education in the sense of control over the life course. The present study examines the life-course pattern in depression by income as well as education, using a longitudinal framework that largely avoids the methodological limitations of cross-sectional analysis.

The results obtained from cross-sectional data might reflect in part mortality selection bias, which might account for some of the convergence in health in later life found in previous cross-sectional work (House et al 1994; Beckett 2000). Because the most fragile or depressed elderly adults, a majority of whom are of lower SES, are more likely to die or to not to participate in a survey, SES differences in health status in later life may appear small or nonexistent, accounting for the later life convergence in health observed in previous studies. Growth curve modeling as a longitudinal framework ameliorates this problem to a significant degree. Individuals who die or otherwise drop out of a sample during the course of the study do not need to be omitted from growth curve analysis (Lynch 2003). Their health trajectories can still be estimated using the available information. The present study enjoys this advantage of growth curve modeling – reducing mortality selection bias to a certain degree.

Finally, in examining education-based life-course patterns, cohort vitiations or effects of historical trend need to be taken into account. Studying the effect of education on mortality over thirty years from 1960 to 1990, Lauderdale's (2001) work indicated that each 10-year birth cohort demonstrates a larger effect of education on survival than do earlier cohorts of the same age, suggesting the increasing importance of education on survival in more recent periods or newer cohorts. After controlling for the cohort effect, education-based gaps in survival extended with increasing age within each cohort, supporting the cumulative advantage hypothesis. Other studies also reported this same cohort pattern in the relationship between education and health or mortality (Lynch 2003; Feldman et al 1989). Increasing structural inequality might explain the stronger effect of education on health in more recent periods - educational credentials' increasing ability to produce inequality in occupation, income, and access to health care (Lynch 2003;; Williams and Collins. 1995). The increasing importance of human capital derived from education might also explain the increasing importance of education in more recent cohorts – e.g. differences in health/medical knowledge by education might be greater in younger cohorts

(Mirowsky and Ross and 2003; Lauderdale 2000). The aging-vector approach used in the present study provides methods to evaluate the effect of historical trend change on the life-course health pattern by education.

The Aging-Vector Approach to Study Life-Course Inequality Patterns

Growth curve modeling (both hierarchical modeling and latent growth modeling) is frequently employed to study child and adolescent development (Raudenbush 2001; Curran 2000). A few recent studies have employed relatively long-term panel data and growth curve modeling to examine inequality in health over the life-course (Hamil-Luker 2004). However, long-term panel studies are rarely conducted (George 2003) due to the tremendous resources they typically require. The advantages of the aging-vector approach have the potential to enrich life-course research. Most of all, it can use relatively short-term (less than 10 years) panel data to study long-term life-course patterns and can assess the effects of contemporary trends on the pattern(s) of interest.

The approach assumes a linear trajectory of a specific outcome over a survey period. The linear trajectory for each 1-year age group or birth cohort is expressed in the form of a vector. An aging vector is the change from one level of an outcome to another over a segment of the life course that begins at one age and ends at another. Every vector has an origin defined as the expected value for individuals of a particular age at the beginning of the segment and a slope defined by the average change expected in the outcome over the following interval of aging. The baseline age variable represents respondent's life-stage at the starting point of the aging trajectory, and the life-stage or age itself might influence the trajectory. Aging-vector graphs generated from the results of estimated linear growth curve models provide a composite image of the long-term life course pattern. The data at baseline need to include a broad range of age groups to cover the long-term life course.

The following section includes several examples of use and interpretation of aging-vectors relevant to the relationship between SES and health over the life course. The mock examples are provided to explain (1) the idea of vectors and their graphs, (2) how to evaluate the two main life-course patterns by SES (i.e., divergence at all ages versus divergence in early adulthood followed by convergence in late adulthood), and (3) how to evaluate the effect of contemporary trend on the life-course pattern.

Mock Aging-Vectors: The Example of Health Inequality

Figure 1 illustrates six possible sets of aging vectors with the same set of origins on several curvilinear cross-sectional trajectories. The vectors represent the predicted values from an hypothetical 10-year study. To simplify presentation, the graphs show only every 10th vector. Each graph shows the differences between two groups in aging vectors and cross-sectional curves. For example, this study considers SES differences in health over the life-course. In Figure 1, the Y-axis might represent the absence of health and the two groups might represent college graduates (lower vectors and cross-sectional curve) and persons with less than a high school degree (higher vectors and cross-sectional curve). As expected from previous research, physical health declines with increasing age in all the cross-sectional curves. All the aging-vectors also show the same patterns across all the adult life-stages or all the 10-year birth cohorts. This study's main interest is health inequality patterns by SES over the life course. Figure 1 shows two different patterns of inequality in cross-sectional curves – divergence and divergence to convergence – and three different patterns in 10-year aging trajectories expressed by vectors – diverging, converging, and constant gaps.

Figure 1

Mathematically speaking, vectors of change need not correspond to the shape of a cross-sectional trajectory. Panels A and B demonstrate cases in which cross-sectional patterns do not correspond to those of the aging-vectors. In panel A, cross-sectional patterns illustrate a consistent diverging gap between those of high SES (i.e., the college graduates) and those of low SES (i.e., those with less than a high school degree), but the aging-vectors indicate the same average increase for all age and SES groups. Therefore, the current aging process in all the different cohorts does not support cumulative advantage of SES in health. How is this possible? It is related to trend differences across cohorts and SES groups. Let's compare levels of the outcome between the cohort who is age 40 at baseline (marked by the circle) and the cohort who is aged 40 at the end of survey (marked by arrowhead) among low SES group. The newer cohort demonstrates lower age-specific level of the outcome (i.e., better health status) at the same age, implying a favorable trend for young adults (arrowhead below circle at 40). Actually, the newer cohorts have lower levels of the outcome at every age group (arrowheads below circles at every age). However, this favorable trend increases with age, such that the largest gap between the two cohorts with 10-year interval (the arrowhead and the circle) is at age 70 in both low SES and high SES groups. If the survey period held a more favorable trend for old adults and low SES persons through, for example, strong social interventions for the group's improvement of health, there might be little cumulative advantage (constant gaps in all groups) in the aging process of the period. If the period trend represents stable historical change in contemporary society, the cross-sectional results showing divergence might misrepresent the changed current and future aging process. In contrast, if the trend in the survey period is very tentative, the aging-vector's pattern might misrepresent the long-term pattern of life-course inequality.

Panel B shows an example of partial inconformity between the cross-sectional patterns and the pattern of aging-vectors. The cross-sectional results indicate a diverging to converging pattern, but the aging-vectors suggest diverging gaps across all adult life stages or age cohorts, supporting the cumulative advantage hypothesis. Trend differences between the two SES groups indicate that the high SES group enjoys a favorable trend across all age groups (the arrowheads are below the circles in all ages). In contrast, the low SES group has unfavorable trends in all the age groups (the arrowheads are above the circles in all ages). The inconformity in old age appears to occur because the favorable trend for the high SES group is much stronger in old age group. For example, the special pattern illustrated in Panel B might occur because certain historical events resulted in a stronger positive effect for high SES elders. In addition, the aging-vectors diverge more than the cross-sectional curves, and it implies that the health inequality problem get worse in future aging population if the current trend is sustained. When we see both the cross-sectional curves and aging-vectors and compare them in terms of effect of trends, we can better capture and understand the aging patterns in current history.

In general, we can expect corresponding patterns between cross-sectional curves and aging-vectors because cross-sectional results tend to reflect primarily age difference as well as cohort fluctuation. If SES influences health status (level), it also tends to influence change in health status. Panel C shows an example of perfect conformity between cross-sectional curves and aging vectors. The cross-sectional curves are exactly overlapped with aging-vectors in all age groups, supporting consistent divergence over the life course. There is no trend (i.e., cohort or period effects), so in the same age, there is no difference of health level between two 10-year interval birth cohorts or the baseline survey year and the last survey year. If both the cross-sectional patterns and the aging vectors reflect consistent divergence, the cumulative advantage hypothesis can be safely argued. As mentioned earlier, one advantage of the aging-vector approach is its ability to provide an approximation of long-term life-course patterns using relatively short-term panel data. As shown in panel C, the connected aging-vectors provide an image of a long-term life-course pattern, and this composite trajectory is called "synthetic cohort trajectory" (Mirowsky and Kim 2004).

Panels D, E, and F provide examples of more realistic patterns. For many research topics, cross-sectional patterns are likely to have a certain degree of conformity with those of the aging-vectors, but not perfect conformity, reflecting a certain degree of trend impact. In Panel D, although there is trend effect, the cross-sectional life-course pattern (divergence to convergence) corresponds to that of the aging-vectors (diverging vectors to converging vectors). In this example, the direction of the trend effect is the same for all age and SES groups – an unfavorable trend in all the groups with same degree (the arrowheads are above the circles with same distance). Historical effect which is same for all cohorts are generally called period effects. This case implies two things. One is that the relative health inequality has the pattern from diverging to converging over the life-course, supporting the age-as-level hypothesis. The other is that the absolute health problem gets worse due to the recent trend, so if the aging-vectors are connected, the future life-course health trajectory would show more steep deterioration in health in aging.

Panel E also shows basic conformity between cross-sectional pattern and aging-vectors' – both support consistent divergence over the life-course. The trend effect is different across age and SES groups – trend disfavoring low SES (especially, in younger adults) and trend favoring high SES in young and middle age adults but not old adults. Recent studies in this topic founded that the effect of education on health is stronger in newer cohorts or recent periods. The especially stronger effect of education in younger adults might be explained by improved quality of education to foster human capital and to increase health knowledge in more recent schooling. Finally, in Panel F, although distinct trend effects by each age-cohort group exist, the patterns of the aging-vectors correspond with cross-sectional patterns (indicating divergence) until early old age. In old ages, cross-sectional results support convergence, while the aging-vectors support divergence. Two possible reasons may account for the inconsistent patterns. One possibility is the existence of a specific trend that strongly disfavors lower-SES elders. Another explanation is mortality selection bias in the cross-sectional results. Assuming the attrition rate of the panel data is not severe, growth curve modeling reduces mortality selection bias. The use of aging-vectors to assess health in later life better represents the declining health of lower SES elders, as implied by panel F, because it poses less of a mortality selection problem.

Specific Aims

This study's aim is to examine the patterns of health over the life course by SES, taking into consideration the effect of historical trends. We expect to find divergence in SES-based health trajectories across all life stages, including later life, lending support to the cumulative advantage hypothesis. Our framework provides judgments about whether the life-course relationships between different health outcomes and different SES factors show different patterns. We intend to answer five specific questions: (1) does health diverge over the follow-up period across levels of education and income for all age groups, supporting the hypothesis of cumulative advantage? Or, does it diverge for the younger age groups but converge for the older ones, supporting the age-as-leveler hypothesis? (2) are there different patterns for physical and mental health? (3) do the patterns differ for education and income?; (4) do the changes over time (aging vectors) follow the cross-sectional patterns, or do they differ in meaningful ways? If they do not show conformity, how should such inconsistency be interpreted?, and (5) is the overall trend pattern consistent with the notion that education is becoming increasingly important to health outcomes (mental health as well as physical health) in more recent cohorts?

METHODS

Sample

Data are from the American's Changing Lives (ACL) Survey, a longitudinal data set based on a nationally representative sample of non-institutionalized adults aged 25 and older in 1986. Sampling, interviewing, and coding for the surveys were conducted by the Survey Research Center of the University of Michigan. Information was obtained through face-to-face interviews with each respondent or a proxy respondent. The overall response rate at baseline was 68%. The initial multistage stratified area probability sample contained 3,617 adults with 100 percent oversamples of blacks and those over the age of 60. As recommended by the ACL study team, all analyses in the present study are adjusted by the final centered post-stratification weight (see Appendix A), which takes into account non-response as well as the sample design. The weighted sample maintains original sample size and corresponds to the July 1986 Bureau of the Census population estimates by sex, age, and region.

This study utilizes three waves of data collected in 1986, 1989, and 1994. Attrition due to death (n=166 in Wave II and n=546 in Wave III) and non-response (n=584 in Wave II and n=509 in Wave III) may lead to differences between the sample and the population it is intended to represent. The three waves of ACL data can be classified into four exclusive groups by follow-up status. The first group is composed of 2,348 respondents (65 percent) who participated in all the three waves, the second represents 519 respondents (14 percent) who participated in the first and the second surveys. The third group is composed of 214 respondents (6 percent) who participated in the first and the third surveys, and the fourth represents 536 respondents (15 percent) who participated in the first wave only. Using an effective missing data imputation methods, the latent growth models in this study include all four groups. The methods employed to deal with the attrition problem are described in the “Sample Attrition” section below.

Measures

Health Measures

This study includes both physical and mental health measures. For physical health, self-rated health and functional health are examined. The multi-indicator latent growth models use each measure as a subscale for an unhealthiness latent factor. For the self-rated unhealthiness subscale, respondents were asked to rate their health along a five-point scale as “excellent” to “poor,” coded 1 to 5, with higher values indicating worse status. Self-reported health is a widely used measure of general health status and is predictive of subsequent disability (Ferraro, Farmer, and Wybraniec 1997; Wilcox, Kasl, and Idler 1996) as well as mortality (Idler and Benyamini 1997). Respondents’ functional health status was assessed with six items, which represent activities of daily living (ADLs) or instrumental ADLs (IADLs). The functional impairment subscale is reconstructed from the 6 items, higher values indicate greater impairment: (4) Most severe level = respondents who are currently in bed or chair or who have a lot of difficulty bathing or cannot bathe, (3) Moderately severe = respondents who have a lot of difficulty climbing stairs or cannot do it or have a lot of difficulty walking or cannot do it but were not in previously defined level, (2) Least severe level = respondents who have a lot of difficulty doing heavy housework or cannot do it but who are not in two previously defined level, (1) No functional impairment = respondents answered no to all of the functional impairment questions.

For mental health, depression is measured with seven items using the Center for Epidemiological Studies Depression Scale (CES-D) (Radloff 1977). Respondents were asked, **“**In the past week,**”** (1) “I felt depressed,” (2) “I felt sad,” (3) “I felt lonely,” (4) “My sleep was restless,” (5) “I did not feel like eating. My appetite was poor," (6) "I felt that everything I did was an effort," (7) "I could not get going." Items are coded from 1 to 3, and the scores indicate: (1) hardly ever (2) some of the time (3) most of the time. The depression scale is the mean response to the seven items. (Alpha reliability of the scale is .783). The multi-indicator latent growth models group the items into two subscales: (1) *sadness* is the mean response to items 1, 2, and 3; (2) *malaise* is the mean response to items 4, 5, 6, and 7.

SES Measures and Control Variables

Education indicates the highest year of formal schooling until 1986. The original variable is coded into two dummy variables representing respondents with a college degree (14%) and those with a high school degree but no college degree (49%), with those who did not complete high school (37%) serving as the reference group. Family income, which is respondents' total annual income before taxes in 1986, was collapsed into a ten-point ordinal variable. The ACL team imputed values for 311 cases and recommended using the imputed income variable for most purposes [1]. The income variable is coded into two dummy variables representing respondents in the highest third (greater than $25,000), the middle third (between $10,000 and $25,000), and the lowest third (the reference group).

For control variables, female is a dummy variable that equals 1 for females and 0 for males. White is coded 1 if the respondent self-identifies as white or Caucasian and 0 otherwise. Because the relationship between age and physical and mental health might be curvilinear, age squared terms will be added to relevant models (Mirowsky and Ross 1999; Ross and Wu 1996). Each age term is modeled as the deviation from age 45, which is a value close to the mean for U.S. adults. This centering method reduces multicollinearity. This age variable (in the first interview) represents not only birth cohort but also respondents' life-stage at the starting point of health trajectories over 8 years in latent growth modeling.

[1] The ACL team conducted this imputation by matching cases with missing income to donor cases, based on education level, marital status, employment status, occupation, and homeownership.

Sample Attrition

Follow-up surveys inevitably lose cases for a variety of reasons, potentially reducing the representativeness of the sample. Table 1 presents descriptive statistics for the variables considered in this study by the four follow-up status groups previously described. The mean values for each variable can be compared across the four groups in Table 1, which provides the foundation for the assessment of possible attrition bias.

Table 1

Latent growth models in this study include all four groups, although three of them contain partial missingness in the outcome variables[2]. Structural equation modeling provides a method to deal with partial missingness (Duncan et al 1999). The present study uses an effective model-based correction method for sample attrition, imputation by Expectation Maximization (EM) (Allison 2001; Little and Rubin 2002). This method uses an iterative procedure that imputes missing values, estimates the model using the filled data set, imputes revised values based on the results, re-estimates the model, and so on. EM imputation is a robust method and greatly improves accuracy over listwise-deletion estimates according to simulation studies (McArdle and Hamagami 1992; Mirowsky and Kim 2004). Even when the MAR (Missing At Random) assumption is violated, it corrects all bias of constant factors in effects and some portion of bias in slope factors in latent growth models.

According to supplemental analyses using multi-logit regression (available on request), baseline physical impairment influenced the probability of dropping out of the study, suggesting that the MAR assumption may be not supported in the EM imputation. In the case of depression, the MAR assumption is violated in the education model but not in the income model. Although

[2] To evaluate correctly the effect of historical trend on aging-vectors, all the cases at baseline need to be included in an aging-vector model to generate unbiased cross-sectional curve by age from the estimation for the constant factor.

there is a possibility of bias due to violation of the MAR assumption, we can evaluate the possible bias' direction with the information in Table 1. As shown in Table 1, all three dropout groups show worse health status and higher depression than group 1, and they also have lower education and income. Therefore, although bias exists after imputation, the bias will result in underestimation of health disparities by SES, leading to conservative estimates of life-course patterns in health as the imputation is more likely to make the change in health appear better in dropouts who have relatively lower SES (Lynch 2004). Depending on the accuracy of the imputed values, the imputation method will also reduce mortality selection bias to a certain degree, because individuals who die or are institutionalized during the study do not need to be omitted from the growth curve models. Their health trajectories can still be estimated using the available information along with the imputed values (Lynch 2003).

Aging-Vector Model

The aging-vector model can be defined as a multi-level growth-curve model, with three characteristics that distinguish it from other types of growth-curve models. First, the aging-vector model's within-person equation has t rather than A_{it} on the right side. Thus the within-person equation describes the effect of aging t years rather than the effect of the differences in age at different times of observation. Second, the aging-vector model has no powers of t other than t^0 and t^1 because vectors are utilized as linear approximations to the curve over each segment of the adult life course. Third, the aging-vector model specifies functions of age at time zero as fixed-effect components of the two between-person equations. Thus, the effect of aging t years depends on age at the time of the study. The age functions can take any form, with any number of them appearing in any combination (Mirowsky and Kim 2004).

Figure 2 shows an aging-vector model or a latent growth model (LGM hereafter) for a health trajectory over 8 years predicted by educational attainment. In this model, we can examine systematic variation in the health trajectory (i.e., baseline level and slope over time) within a person as a function of background variables including age and education (notice that age at baseline explains the health change factor). The health outcomes used for this study are all subjective measures, so latent growth models having multiple indicators are more appropriate than a hierarchical approach to growth curve modeling. In Figure 2, the health latent factor in each wave has two observed indicators- self-rated health and physical impairment. This multi-indicator LGM reduces measurement error and provides more accurate estimates than single-indicator LGM (Mirowsky and Kim 2004). To define the slope as linear, the factor loadings are set to 0, 3, and 8 - implying proportional health change by year. This model allows for a residual correlation between health change over time and the constant over time. By allowing correlation between the residuals in the two equations (for the constant and for the change), the model adjusts the estimated effects on each factor for the level of the other (McArdle and Hamagami 1992). It also helps correct for apparent regression to the mean produced by random measurement error or by floor and ceiling effects -that is, when high scores can decline more than low scores can, and vice versa (Mirowsky and Kim 2004; Lynch 2003).

Figure 2

Using three waves of panel data, this study examines the intra-individual trajectories of physical and mental health over eight years focusing on differences by SES. In cross-sectional models, a changing gap (such as divergence) in health over the life-course reflects cohort difference as well as age difference. The aging-vector model as a longitudinal model indicates how health status within a person changes according to SES over eight years of developmental time. With this eight years' longitudinal framework, we can predict or judge change in the life-course pattern (such as divergence) attributable to the aging process.

If education or income at baseline has significant effects on the slope for the health measures, this indicates that the SES-based gap in health is changed by the aging process. For example, if the group of college graduates shows a significantly lower slope in depression than the group with less than a high school degree, it implies that the depression gap diverges net of other factors including age in 1986 (or birth cohort). If the gap diverges regardless of age (or cohort), it supports the life-course divergence pattern suggested by the cumulative advantage hypothesis. It assumes that the pattern over 8 years can be extended (or applied) to entire life-course pattern. To the extent that the additional change over 8 years accumulates over the life-course, the gap would diverge more and more. The model in Figure 1 includes interaction terms between baseline age and educational attainment as well as education variables themselves. Significant positive effects for the interaction terms would indicate that the diverging pattern in earlier adult life-stages changes to a converging pattern in later life.

RESULTS

Physical Health

Table 2 shows the results from two aging-vector models predicting physical health. The first latent growth model examines the effects of education and the second LGM estimates the effects of family income. In the education model, college graduates show significantly better health at baseline (constant) and a smaller slope (change or growth rate) net of socio-demographic factors including age at baseline, compared to the group with less than a high school degree. This suggests that educational attainment has a cumulative effect on health regardless of cohort or age (life-stage), resulting in a diverging gap over the 8 year aging process in all life-stages (or in all cohorts) – the interaction between age and college degree on the slope for health is not significant, implying that the diverging pattern is consistent across all life-stages, including later life. The mid-education group demonstrates the same patterns as college graduates but with a smaller effect size.

Table 2

The pattern of results from the income model is consistent with that of the education model. Like those with the highest levels of education, the high-income group (the highest one-third) shows significantly better health at baseline and a smaller slope net of age at baseline, compared to the low-income group (the lowest one third). This model indicates that the high-income income group enjoys a cumulative advantage in health, resulting in a diverging gap over 8 years of aging across all life-stages – the interaction effect between age and income is not significant. The middle-income group also shows same patterns as the high income group's. In the income model, the effect of education (e.g. college degree) on the change in health is reduced by about 38% (from -.021 in the education model to -.013), implying that the education-based diverging gap over the aging process is explained to a significant degree by the income-based divergence in health. However, the non-economic advantages of education still play an important role in the accumulation of health advantage (62% of the original effect remains and is significant).

The aging-vector graphs shown in Figure 3 provide summaries of the LGM results in Table 2. Each arrow represents the predicted origin and change in health for a 1-year birth cohort. The horizontal axis shows the cohort's age at the beginning and end of the survey period. The vertical axis shows its predicted health at the beginning and end. Mean (weighted) values of each of the control variables are used to generate predictions of the vectors. To simplify the figure, vectors are shown for every eighth age group. Health at baseline for those 25 years of age and older in 1986 was calculated by substituting 25 for age in the equation predicting the constant, multiplying by the respective coefficients, and summing the products. Average annual change (or slope) was calculated in a similar manner using the change equation, multiplied by 8, and then adding that 8-year change in health to the baseline health, yielding the health predicted at the end. The same procedure was followed for ages 33, 41, 49, and so on (Mirowsky and Kim 2004).

Figure 3

A series of vectors in the upper side show the health trajectories of the higher SES group, and the vectors in the lower side show those of the lower SES group. Across all age-cohort groups or life-stages, we find diverging health gaps by education and income over the 8-year aging period.

Trend effect or cohort variations might influence the diverging patterns. In left graph of Figure3, young adults have unfavorable trend, especially, in persons less than high school – e.g. the newer cohort has higher (worse) age-specific levels of health status at age 33, and it also implies trends disfavoring young adults between 1986 and 1994. In old adults, there exist still unfavorable trend to persons less than high school but a little favorable trend to college graduates. In aging-vector graphs, connecting the origins of arrows provide the cross-sectional curves in health[3]. Both cross-sectional curves (imagine curves connecting the origins of arrows) and aging-vectors across all life-stages show diverging pattern, so it supports cumulative advantage hypothesis over the life course. Trend effect appears to contribute to the diverging gap by education in physical health.

[3] The within-person constants predicted using all cases are essentially unbiased by attrition, so predicted curve from the equation represent correctly cross-sectional life-course pattern by SES. Using only complete cases, or only cases with some followup data, creates gross bias in the estimated effect of age on the constant.

In the comparison between persons less than high school and high school graduates (and less than BA degree), both cross-sectional curves and aging-vectors across all life-stages show diverging pattern. Trend effect appears to contribute to the divergence. The hypothesis that the effect of education is stronger in newer cohort or recent period is supported in the difference of trend effect across education level. Although period specific effect (between 1986 and 1994) made unfavorable trend in most of age-SES groups, the degree of unfavorable trend in college graduates is relatively small, compared to that in persons less than high school, and the older groups have even favorable trend. In high school graduates (and less than BA degree), the hypothesis is supported mainly in younger age groups – there is little trend difference in older age groups between persons less than high school and high school graduates.

In right graph of Figure 3, both cross-sectional curves and aging-vectors across all life-stages show diverging pattern. All the groups show similar trend pattern – unfavorable trend to all of them but a little more unfavorable trend to low income group. These results support cumulative advantage hypothesis of income in physical health. All the change patterns in physical health by education and income suggest that the health gap will diverge more and more in future aging population if the current trend is maintained. To the extent that the diverging gaps over 8 years in all life-stages accumulate over the life-course, the health gap will diverge more and more, resulting in severe health inequality in the future elderly.

Mental Health

Table 3 presents the results from the two aging-vector models predicting depression. In the education model, college graduates show significantly lower initial depression levels and lower depression slope, compared to the group with less than a high school diploma, implying a diverging gap through 8 years of aging across all life stages. The interaction term between age and college degree is not significant. In left graph of Figure 4, no trend effect exist among persons less than high school degree, but in college graduate, all cohorts enjoy strong favorable trend with similar degree. Cross-sectional curves show diverging pattern, but not significant[4]. Aging-vector show diverging patterns in all life stages, and trend effect appears to contribute the divergence. Along with the contemporary trend of favoring higher educational attainment, cumulative advantage hypothesis is supported.

However, the diverging gaps between high-school graduates and persons with less than a high school diploma change into converging gaps in later life, (or within the older cohorts) as shown in Figure 4. In the comparison between persons less than high school and high school graduates, trend favors high school graduates (and less than BA degree) in younger cohorts but disfavors them in older cohorts. This result extends the previous studies' findings that education's effect on health becomes stronger in more recent period. In mental health as well as physical health on which previous studies focused, college degree play more beneficial role in depression in more recent period. In case of mid-level educational attainment, it plays more beneficial role in younger age groups recently. In old age groups, high school degree's effect on health becomes less strong in more recent period. One method to compare education's effect difference between 1986 and 1994 is comparing the gaps between two baseline cross-sectional curves (connecting the origin of arrows) with those between two last-survey cross-sectional curves (connecting the arrowheads). Greater gap means stronger effect. Therefore, the convergence appears to be the result of this trend effect or cohort variation.

Table 3

[4] In the all aging-vector models of this study, the interaction terms between age squared and SES factors are not included in the models because they are not significant.

For the income model, the high income group does not show a significantly lower slope for depression than the low income group. The cumulative advantage of income on reducing depression might not be as strong as the advantages accumulated as a result of education. Moreover, shown in Figure 4, the weak diverging gaps change to convergence in later life. Because income may be time-variant, we examined another aging-vector model considering income change and persistence (analyses not shown, but available on request). For this model, 3,081 cases were used that provided any follow-up information and generated three dummy variables of persistently higher income (above the median over time), rising income, and falling income – with the reference category being the persistently lower income (below the median over time). The model was not weighted because the ACL data do not provide appropriate weight variable for the 3,081 cases. The results indicate that the persistently higher income group shows significantly lower slope than the persistently lower income group until age 75; after that, the diverging gaps change into convergence, resembling the pattern shown in Figure 4.

In Figure 4, in case of low income group, trend favors all age groups, especially, old age groups, but in case of high income group, trend favors younger age groups more strongly. In older ages, low income groups have a little more favoring trend, compared to high income elders. Although this trend effect appears to contribute to the convergence in old age in some degree, the mechanisms of age-as-leveler might also operate. As shown in Figure 4, the convergence occurs because the low income group's depression does not increase by much. This is not an artifact of attrition selection bias because MAR assumption is not violated in EM imputation of this latent growth model. There is an appropriate theoretical explanation for this pattern, however. Maturity and coping abilities that accrue with age as a result of life experiences might operate as a leveler that reduces the income-based gap in depression among the elderly (Gove et al 1989; Mirowsky and Ross 2001).

Figure 4

In sum, the cumulative advantage hypothesis is completely supported in the relationship between physical health and SES. Both education and income generate diverging gaps through the aging process across all cohorts or all life-stages, including later life. In case of depression, the results are mixed. Education leads to a consistent cumulative advantage for depression, but income's effect is relatively weak and appears to diminish in later life. This distinct findings suggest the possibility of different life-course effects of different SES factors on different health outcomes. Nevertheless, overall results confirm the persistent and cumulative health inequality by SES over the life-course.

DISCUSSION

In this study, we used an aging-vector approach to examine differences in health trajectories by education and income over time in a broad range of age groups. Our approach provides a composite image of the entire adult life-course pattern from segmental health trajectories at all adult life stages. Moreover, it allows trend effects to be confirmed in each age/SES group. In sum, we find a consistent diverging SES-based gap in physical health over the life course, lending support to the cumulative advantage hypothesis. Our models indicate divergence in physical health across all age groups, including older age, across levels of education and income in both aging-vectors and cross-sectional curves. We also find divergence in levels of depression across the life course by education. Taken together, these diverging patterns support the cumulative advantage hypothesis and also suggest that health inequality will grow in future aging populations if current trends favoring higher SES persons is sustained.

In the case of the life-course relationship between income and depression, significant cumulative advantage is observed (supported) only when persistence or duration of income status is taken into account; that is, the persistently higher income group shows cumulative advantage, compared to the persistently lower income group. Furthermore, we find that the divergence in depression by income found throughout early and middle adulthood changes into convergence in later life. Although a trend effect partially contributes to later life convergence, maturity as a leveling mechanism in aging may operate to prevent worsening depression in lower income elders. The hypothesis of age-as-leveler focusing on biological frailty is not supported in the present study, as shown in the later life pattern of physical health. However, the old age convergence by income in depression might be explained by a mechanism related to aging. According to Gove and colleagues (1989), age indicates increasing maturity because as individuals get older their self-concepts include more positive features. Moreover, older adults have more positive self-evaluations such as higher life satisfaction and higher self-esteem. Mirowsky and Ross (2001) found that the effect of economic hardship on depression diminished in later life and explained the moderating effect of age with the increasing maturity and coping abilities in later life. Convergence in maturity and coping abilities might generate the converging gap in depression by income among older adults observed in our model.

Consistent with previous research, our results suggest that the impact of education on health is stronger in more recent cohorts or in more recent periods. We find that the effect of education on both physical and mental health is stronger in more recent periods. For example, a college degree is more beneficial in more recent periods (trend favoring the college graduates) for all age groups and the trend appears to be especially salient for depression. However, mid-educational attainment appears to be more beneficial in more recent periods in younger age groups, but not older age groups. One possible explanation for the stronger effect of education within younger age cohorts might lie in the improvement over decades in the quality of education (especially, in mid-educational institutions) to foster human capital and to increase health knowledge (Lynch 2003; Lauderdale 2000). Structural inequality based on education's credentials seems to influence all age groups similarly. If the current trend advantages those with college degree, the advantage might be applicable to the older age cohort's educational degree same as the younger age cohort's. And, that might explain that the college degree is more beneficial in more recent period in older adults as well as younger adults.

Both aspects of education, human capital and structural advantage, seem to play important roles in health inequality over the life course. As previously described, income-based divergence accounts for about 40% of the education-based divergence in physical health over the life course. For depression, income explains only 20% of the education-based divergence over the life course. If we assume that the increasing income gap generally reflects the structural advantage aspect of education, the structural advantage aspect of education might play relatively important role in physical health inequality, while the human capital aspect of education (e.g. fostered psychosocial resources such as sense of control, coping skills, and social support) might play a more important role in mental health inequality over the life course.

Finally, our study confirms SES-based cumulative advantage in physical health across all life-stages and in mental health across most life-stages. An additional process that may operate over the life course, acting to amplify cumulative advantage or disadvantage in aging is "feedback amplification" between physical health and mental health (Mirowsky and Ross 2003). Feedback amplification refers to the mutually reinforcing effects of physical and mental health. For example, a decline in physical health tends to increase depression, and depression tends to negatively affect physical health (Farmer and Ferraro 1997; Aneshensel et al 1984). If this vicious cycle operates over the life-course and especially in later life, the cumulative advantage and disadvantage in aging would result in increasingly divergent gaps in both physical and mental health by SES.

Methodological Issues

Two methodological issues related to our conclusions that merit further discussion are selection bias and cohort effects. Despite a reasonable rate of sample attrition and our use of a relatively robust method for imputing missing data, the potential for bias exists in our results because the MAR assumption was not completely satisfied in certain imputation processes. However, the possible bias is most likely to produce underestimation of the SES-based divergence in health, or conservative estimates of inequality in health by SES, as shown in Table 1. Therefore, it can be safely argued that the consistent diverging patterns found in our study are not an artifact of selection bias.

Built into the aging-vector approach is the assumption that life-stage or age at baseline is a significant force of trajectories of change, while taking into account the possibility of cohort variation in the aging trajectories. It appears to be appropriate to think that cohort effects are added to the basic life-stage patterns of the health trajectory. It is inherently impossible to disentangle age effects from cohort effects because age at baseline is linearly determined by birth cohort. However, the aging-vector approach is capable of capturing the potentially substantial role of historical trends in life course trajectories[5]. Historical effects can influence the strength of certain inequality among different cohorts. The aging-vector approach evaluates possible variations in the inequality due to cohort or historical effects, confirming trend effects that favor

[5] It is not possible to disentangle the effect of age and that of cohort on health change, but the effect of historical trend on health level can be evaluated with adjusting for age. Based on the evaluation, the effect of historical trend on health change can be approximately judged.

or disfavor certain subgroups. For example, for the depression trajectories in this study, the education model showed convergence in older age groups between persons of mid-educational level and persons with less than a high school degree. As we interpreted in the 'Results' section, historical trend effect appears to contribute to the convergence. In older age cohorts, mid-educational attainment might have little difference with lower educational attainment in terms of benefits to mental health.

The aging-vector model can express various patterns in inequality across all life stages. The aging-vector model in this study can express 9 patterns of inequality over the life course, distinguishable by statistical significance – (1) consistently diverging gaps (or vectors), (2) diverging to constant gaps, (3) diverging to converging gaps, (4) constant to diverging gaps, (5) consistently constant gaps, (6) constant to converging gaps, (7) converging to diverging gaps, (8) converging to constant gaps, and (9) consistently converging gaps. More complex patterns can be expressed with the inclusion of higher-powered baseline age terms and related age interaction terms, although the model presented in this study is likely to be appropriate for many topics. The aging-vector approach can be applied to many life-course research topics and it can provide a new window for the study of stratification over the life-course, including life-course patterns of various health outcomes, well-being indices, psychosocial resources, or economic status by education, occupation, gender, race, ethnicity and so on.

A final methodological issue to be mentioned is the potential sensitivity to the survey period of the aging vector approach, due to the utilization of relatively short-term panel data. The aging-vector approach provides a composite image of long-term trajectories based on the segmental aging trajectory during the survey period, and it also evaluates trend effects based on the trend during the survey period. If a relatively short survey period does not adequately represent the contemporary trend, generalization of the findings to predict future trajectories is limited. However, the ability of the aging-vector approach to make long-term predictions based on relatively short-term panel data, which is much more available, is one of its main advantages. If additional studies using data of different periods are conducted and yield similar patterns of results, the aging-vector approach's possible period sensitivity can be eliminated as a significant limitation.

Conclusion and Practical Implications

In conclusion, the consistent divergence in physical health by income and education observed in our study lends support to the cumulative advantage hypothesis. The education-based gap in depression also shows divergence over the life course, but the income-based gap in depression shows convergence in old age, supporting the age-as-level hypothesis based on increasing maturity. A trend effect favoring higher SES groups (especially in younger age cohorts) partially contributes to the divergence over time, supporting the notion that education's effect is stronger in more recent periods or newer cohorts. The aging-vector approach employed in this study provides a comprehensive understanding of issues related to life-course health inequality, based on the contemporary trend.

Our examination of different health outcomes by different SES factors reveals that life-course patterns in health may differ by various dimensions of SES and health, suggesting the necessity of studying the life-course relationship between diverse SES factors and health outcomes. Future work will examine the life-course relationship between work status (quality of daily activity) as a fundamental cause of health inequality proximal to SES and psychological distress.

The results of this study strongly suggest the possibility of increasing health inequality in the future aging population. To the extent that the current trend of divergence in health across each life stage is accumulated over the life course, inequalities in health will be more pronounced in the future aging population. This life-course framework of health inequality highlights the importance of social intervention to reduce the gap in accessibility to education or the gap in financial resources in early life to prevent further divergence in health over the life course.

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TABLE 1. 1986 Means with Standard Deviations in Parentheses (Weighted)

	Total Sample	Follow-up Sample			
	1986	Group1 Waves 1, 2 & 3	Group2 Waves 1 & 2	Group3 Waves 1 & 3	Group4 Wave 1 Only
White	.835	.864	.731	.817	.759
	(.371)	(.343)	(.444)	(.387)	(.428)
Female	.529	.546	.545	.450	.456
	(.499)	(.493)	(.499)	(.499)	(.499)
Age	47.111	45.083	55.541	45.939	52.466
	(16.446)	(14.863)	(18.737)	(15.432)	(19.919)
Education	12.366	12.830	11.234	11.541	11.039
(Schooling)	(3.136)	(2.857)	(3.339)	(3.338)	(3.659)
Family Income	30.450	33.490	23.030	26.440	21.050
($1,000)	(24.043)	(24.469)	(22.726)	(21.101)	(19.618)
Functional	1.271	1.189	1.554	1.274	1.506
Impairment	(.705)	(.594)	(.943)	(.728)	(.913)
Self-rated	2.300	2.180	2.690	2.380	2.670
Unhealthiness	(1.068)	(.984)	(1.174)	(1.103)	(1.250)
Depression	1.460	1.441	1.508	1.489	1.522
	(.402)	(.391)	(.426)	(.411)	(.429)
Percentage (%)	100	71.3	10.1	6.2	12.4

TABLE 2. Unhealthiness Constant and Change Regressed on Socioeconomic Status Factors and Their Interactions with Age : Multi-Indicator Latent Growth Models with Missing Data Imputed by Expectation Maximization (Metric Coefficients with Standard Errors in Parentheses.)

	Education Model [a]		Income Model [b]	
Variables	Constant	Change	Constant	Change
Female	.077 ***	-.004	.045*	-.005
	(.022)	(.003)	(.022)	(.009)
White	-.030	-.017***	.006	-.016***
	(.029)	(.004)	(.029)	(.004)
Age	.155 ***	.005*	.152***	.005**
	(.015)	(.003)	(.015)	(.002)
Age^2	2.918 ***		1.887***	
	(.397)		(.402)	
College Degree [c]	-.308 ***	-.021***	-.219***	-.013*
	(.037)	(.005)	(.037)	(.005)
High School to	-.204 ***	-.014**	-.141***	-.008 [H]
Any College [c]	(.030)	(.004)	(.029)	(.004)
High Income [d]			-.287***	-.014**
			(.035)	(.005)
Middle Income [d]			-.188***	-.016**
			(.035)	(.005)
Age H	-.053 *	-.003		
College [c]	(.022)	(.003)		
Age H	-.051**	.003		
Mid-education [c]	(.016)	(.002)		
Age H			-.070***	-.000
High Income [d]			(.018)	(.003)
Age H			-.018	.000
Middle Income [d]			(.017)	(.002)
Intercept	2.389***	.055***	2.550***	.061***
	(.037)	(.005)	(.040)	(.006)
Residual Variance	.279***	.002***	.278***	.002***
	(.015)	(.001)	(.014)	(.000)
Residual Correlation	-.317 ***		-.347 ***	
R^2	.295	.109	.310	.086

[H] $P < .10$, * $p < .05$, *** $p < .01$, *** $p < .001$ (2-tailed tests) ; N= 3,617

[a] Fit indexes: χ^2=295.673, df=40, $p < .001$; BBN=.984, NNFI=.965, SRMR=.018, RMSEA=.042.

[b] Fit indexes: χ^2=364.271, df=48, $p < .001$; BBN=.984, NNFI=.961, SRMR=.018, RMSEA=.043.

[c] Compared to less than high school. [d] Compared to low income.

Age is modeled as $(Age-45)10^{-1}$, and Age^2 is modeled as $(Age-45)^2 10^{-4}$.

TABLE 3. Depression Constant and Change Regressed on Socioeconomic Status Factors and Their Interactions with Age : Multi-Indicator Latent Growth Models with Missing Data Imputed by Expectation Maximization (Metric Coefficients with Standard Errors in Parentheses.)

	Education Model [a]		Income Model [b]	
Variables	Constant	Change	Constant	Change
Female	.087 ***	-.005	.090***	-.006***
	(.011)	(.003)	(.012)	(.002)
White	-.076 ***	.001	-.066 ***	-.001
	(.015)	(.002)	(.017)	(.002)
Age	-.025 ***	.002*	-.137***	.002 [H]
	(.008)	(.001)	(.008)	(.001)
Age^2	1.259 ***		1.050***	
	(.197)		(.215)	
College Degree [c]	-.161 ***	-.010***	-.122***	-.008**
	(.019)	(.003)	(.021)	(.003)
High School to	-.083 ***	-.007***	-.058***	-.007**
Any College [c]	(.016)	(.002)	(.016)	(.002)
High Income [d]			-.132***	-.001
			(.020)	(.003)
Middle Income [d]			-.061**	-.000
			(.020)	(.003)
AgeHH	-.001	.001		
College [c]	(.011)	(.002)		
Age H	-.013	.004***		
Mid-education [c]	(.008)	(.001)		
Age H			.012	.002
High Income [d]			(.010)	(.001)
Age H			-.009	.006***
Middle Income [d]			(.009)	(.001)
Intercept	1.475***	.000	1.541***	.001
	(.019)	(.003)	(.022)	(.003)
Residual Variance	.075***	.001***	.084***	.001***
	(.004)	(.000)	(.005)	(.000)
Residual Correlation	-.315 ***		-.386 ***	
R^2	.095	.072	.116	.072

[H] $P < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$ (2-tailed tests) ; N= 3,617

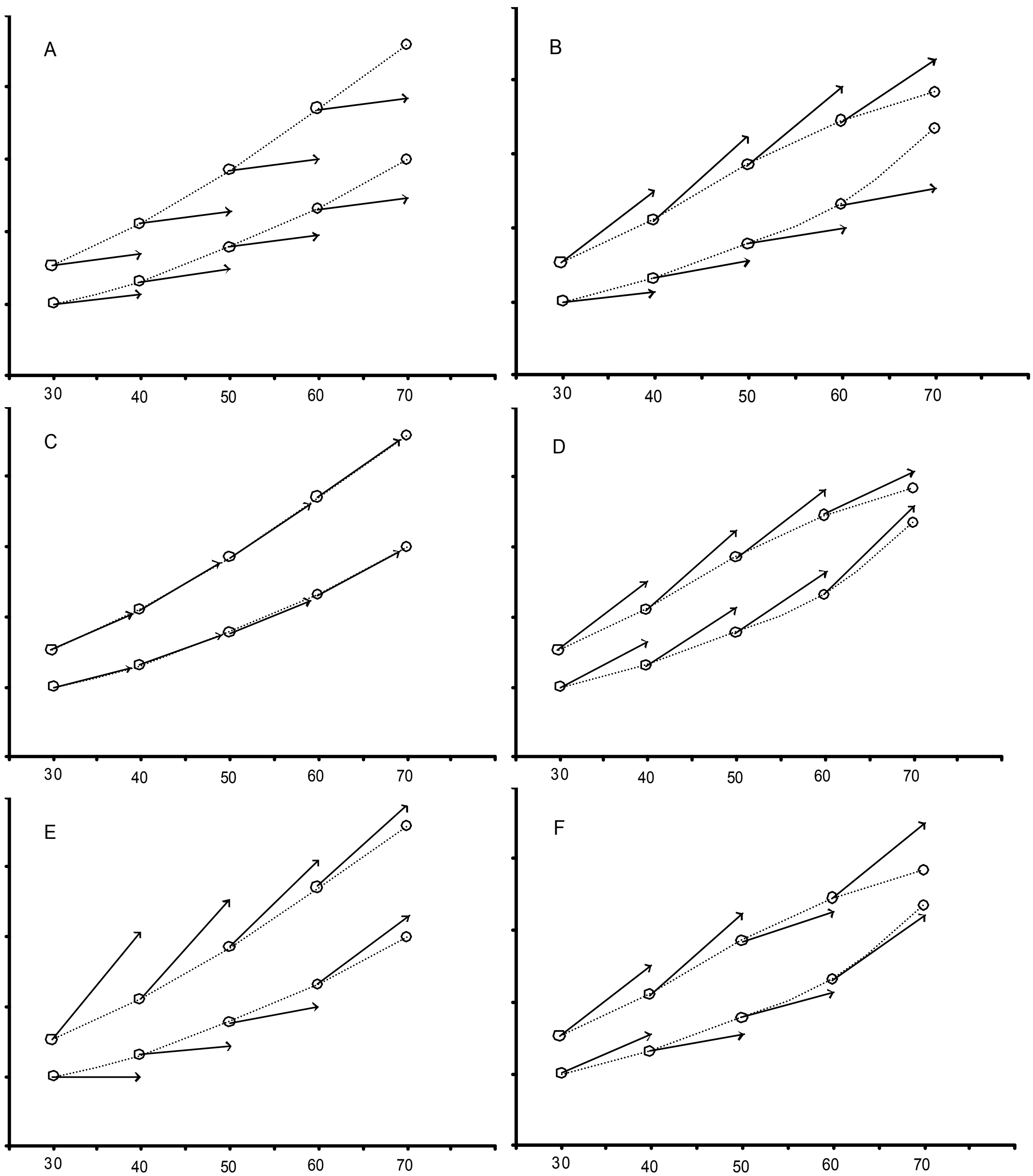
[a] Fit indexes: ^{2}=210.256, df=40, $p < .001$; BBN=.992, NNFI=.987, SRMR=.014, RMSEA=.034.

[b] Fit indexes: ^{2}=243.873, df=48, $p < .001$; BBN=.992, NNFI=.985, SRMR=.013, RMSEA=.034.

[c] Compared to less than high school. [d] Compared to low income.

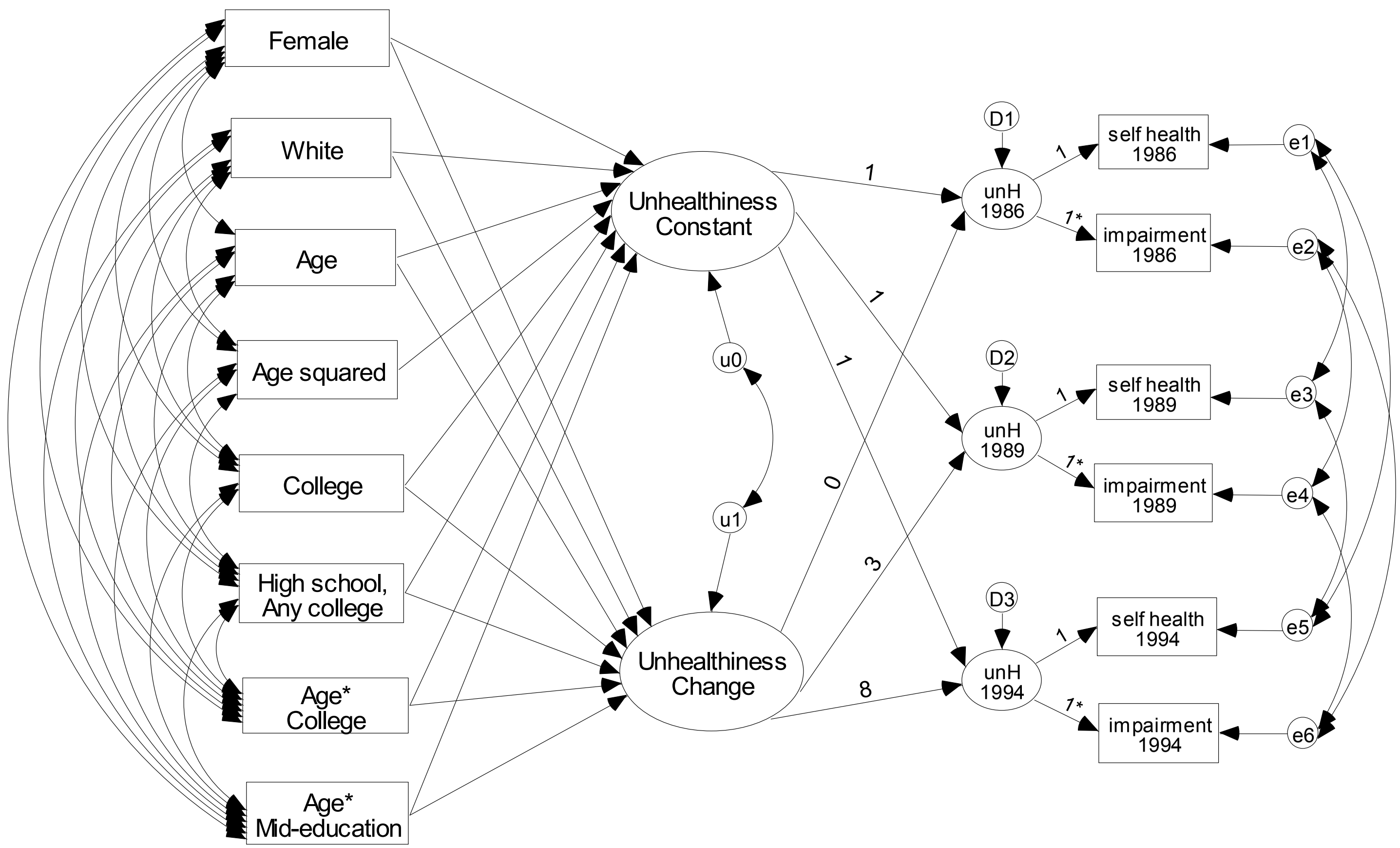
Age is modeled as $(Age-45)10^{-1}$, and Age^2 is modeled as $(Age-45)^2 10^{-4}$.

Figure 1. Aging-Vector Graphs by Social Status Illustrating Six Possible Relationships Between a Cross-Sectional Trajectory and Vectors of Change over a 10-Year Followup.



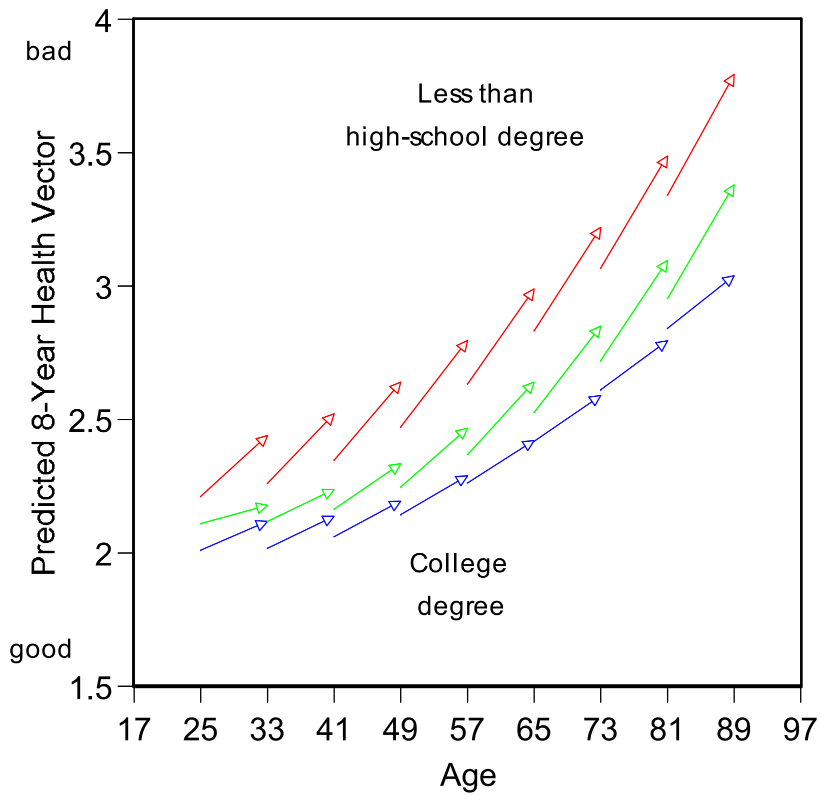
Note: X-axis represents age, and Y-axis represents unhealthiness in our study.

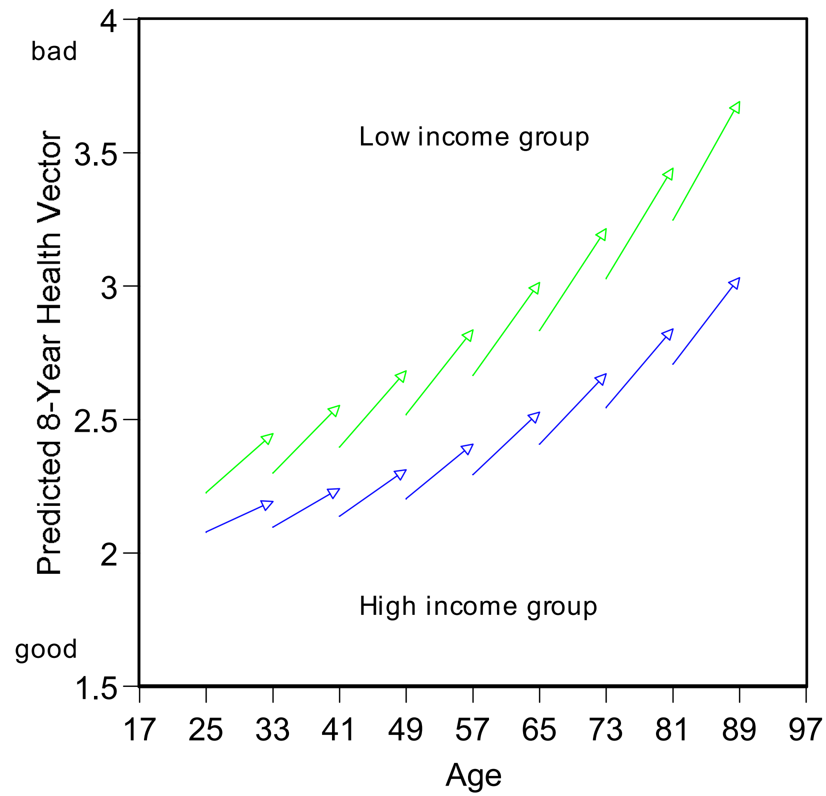
Figure 2. Aging-Vector Model for Unhealthiness over Eight Years by Educational Attainment.



Note: This multi-indicator latent growth model allows correlation of measurement errors across time.

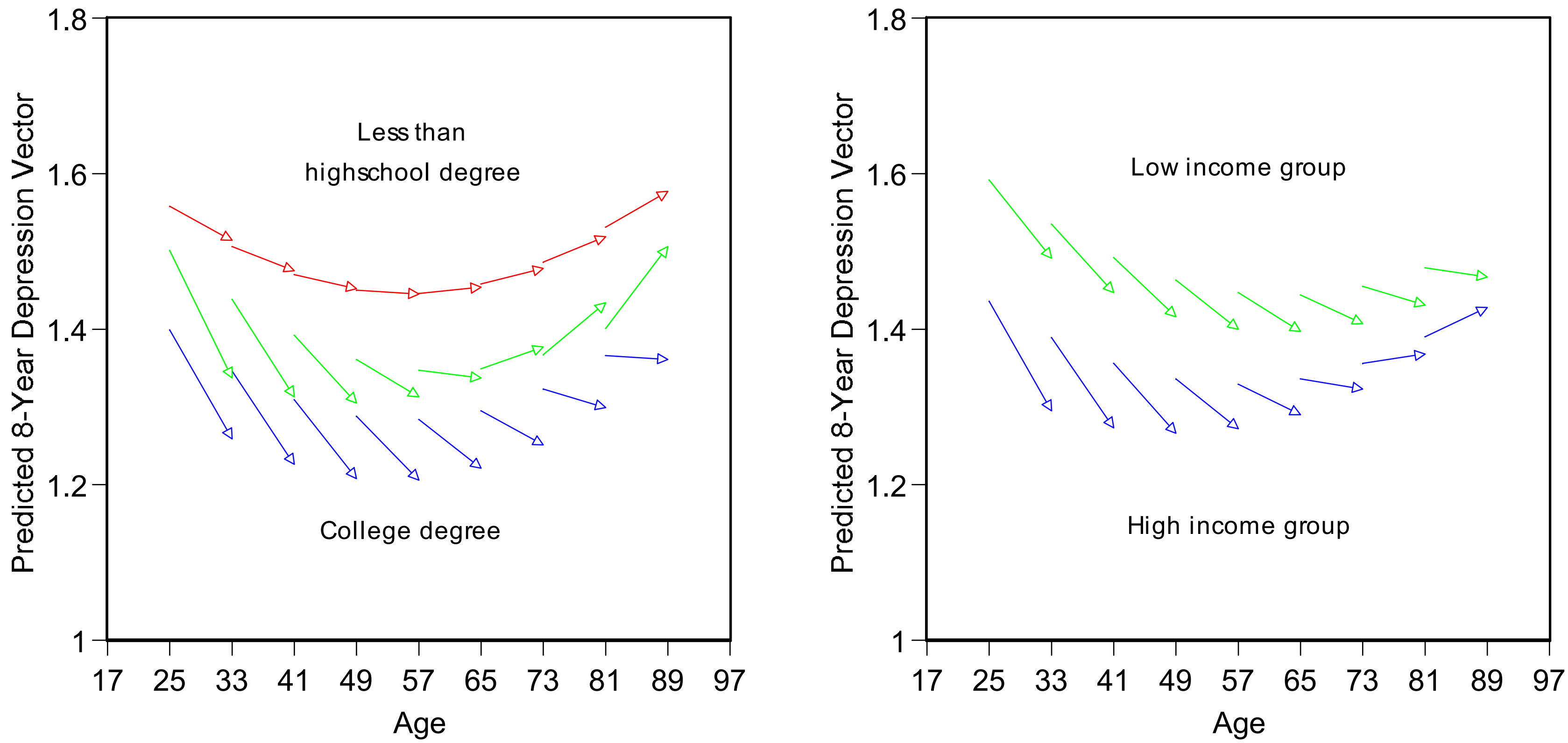
Figure 3. Predicted 8-Year Aging Vectors of Unhealthiness by Educational Attainment and Family Income.





Note: N=3,617; College degree group (n=500), High-school degree to less than college degree (n=1,768), Less than high-school degree group (n=1349), High income group (the highest one third; n=1254), Low income group (the lowest one third; n=1,176).

Figure 4. Predicted 8-Year Aging Vectors of Depression by Educational Attainment and Family Income.



Note: N=3,617; College degree group (n=500), High-school degree to less than college degree (n=1,768), Less than high-school degree group (n=1349), High income group (the highest one third; n=1254), Low income group (the lowest one third; n=1,176).