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Intercohort Trends in the Relationship Between Education and Health

Examining Physical Impairment and Depressive Symptomatology

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Objective: This study examines whether educational differentials in functional and mental health are greater in more recent cohorts in the United States. **Method:** This study utilizes latent growth-curve modeling to examine intercohort trends in physical impairment and depressive symptomatology for three educational subgroups, using panel data (1986-1994) based on a national probability sample of 3,617 U.S. adults. **Results:** Among those with less than a high school diploma, the 8-year newer cohort demonstrated higher physical impairment at the same age, implying an unfavorable trend. College graduates and high school graduates enjoyed favorable trends in mental health, and the trends were different across age groups within certain educational groups. **Discussion:** This study provides evidence that the education-based disparity in health is increasing, but there are variations in the trend depending on health outcomes. These results argue for the necessity of examining trends in education and health using diverse health outcomes.

Keywords: *cohort patterns; education; functional health; mental health*

As public health researchers focus on socioeconomic status (SES) as a fundamental cause of disease (Link & Phelan, 1995), health policy makers have a growing interest in reducing SES-based disparities in health

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(U.S. Department of Health and Human Services, 2000). Educational attainment has been considered an essential element of SES in generating a health or mortality disparity in the current U.S. population (Mirowsky & Ross, 2003). The question is whether the education-based disparity in health is increasing or decreasing. Several researchers have examined whether the effect of education on mortality or self-rated health is stronger in more recent birth cohorts (Lauderdale, 2001; Lynch, 2003, 2006), whereas others have examined whether the effect of education on mortality is stronger in more recent periods (Feldman, Makuc, Kleinman, & Cornoni-Huntley, 1989; Pappas, Queen, Hadden, & Fisher, 1993; Preston & Elo, 1995). In general, these studies indicate a greater effect of education on mortality or self-rated health in more recent cohorts or periods.

Although mortality and self-rated health are important measures to examine health inequality, other major health outcomes such as functional and mental health need to be examined in order to provide a more comprehensive understanding of cohort or period trends in the relationship between education and health. Using panel data (1986–1994) based on a national probability sample of U.S. adults, the current study uses latent growth-curve modeling to examine whether intercohort trends exist that favor individuals with more education or disfavor those who are less educated. For example, 8-year newer birth cohorts among college graduates might have better health than 8-year earlier cohorts at the same age, suggesting a favorable trend for college graduates. An intercohort trend in this study indicates a progressive change in the level of an outcome, such as health, at the same age across cohorts. The direction and size of the change or trend reflects cohort difference or period difference (e.g., the difference between 1986 and 1994) because only age is fixed (i.e., the sum of cohort effect and period effect).

Intercohort Trends in the Relationship Between Education and Mortality or Health

Examining the effect of education on mortality from 1960 to 1990, Lauderdale's (2001) work suggested that each 10-year birth cohort demonstrated a larger effect of education on survival compared to earlier birth cohorts of the same age, signifying the increasing importance of education on survival among more recent cohorts. Additional studies also reported this same cohort or period pattern in the relationship between education and self-rated health or mortality. Lynch (2003) found a greater effect of education on self-rated health in more recent cohorts, using repeated cross-sectional surveys for the period from 1972 to 1993. Feldman et al. (1989) found increasing educational differences in mortality between 1960 and 1971–1984 for middle-aged and older White men. Pappas et al. (1993) found an increasing educational difference in mortality between 1960 and 1986 for persons 25 to 64 years of age. Another study utilized a deprivation index to examine mortality trends at the county level and also found a widening gap by SES between 1980 and 2000 (Singh & Siahpush, 2006).

The present study examines functional and mental health in order to see whether the education-based disparity in health increased between 1986 and 1994. Few previous studies have examined functional health to investigate the education-based trend (Freedman & Martin, 1999; House, Lantz, & Herd, 2005), and no study has examined mental health in this topic. One study included an examination of functional limitations among older adults from 1984 to 1993 and found no trend (Freedman & Martin, 1999). However, Clark (1997) found a widening racial gap in disability among older adults, suggesting the possibility of a widening educational gap in disability because racial minorities tend to be less educated. Finally, House et al. (2005) found a cohort trend favoring more educated adults of certain age groups in terms of functional limitations, but they did not examine the cohort trend systematically. The current study systematically examines the trends in both mental and functional health for all adult age groups.

Three potential contributions of this study can be specified. First, in this area of study, previous investigators have focused on mortality and self-rated health, but trends in education and health might differ, depending on the health outcomes selected for study. This study is intended to reveal potentially different trends across diverse health outcomes. Moreover, examining depressive symptomatology and functional health may be of particular importance in this area. As the World Health Organization has suggested, mental health is an important dimension of health, and depressive symptomatology may be a sensitive indicator for the study of increasing health inequality because it can be more responsive to recent increases in life quality disparity. In addition, physical impairment may be one of the best indicators to study increasing health inequality resulting from inequality in health care because degree of physical impairment is closely related to health care utilization.

Second, this study provides more comprehensive results and a richer understanding of the trends in health, relative to previous studies. Most previous studies examined the changing effect of education, or changes in certain inequality indexes over time, without attempting to identify the trends within each educational subgroup. The present study examines the trends in three educational subgroups and reveals underlying patterns of increasing disparity (e.g., trends favoring college graduates or trends disfavoring those with less than a high school diploma).

Third, the current study utilizes graphs and the trend function to effectively present the intercohort trend and test the intercohort trend statistically (Mirowsky & Kim, 2007). The trend function provides two statistical tests for the trend: (a) a test to identify a significant trend at a reference age and (b) a test to assess for significant differences in trend rate across ages. Consequently, this study may elucidate potential age variations in the trends (i.e., different trends across age groups within each education group).

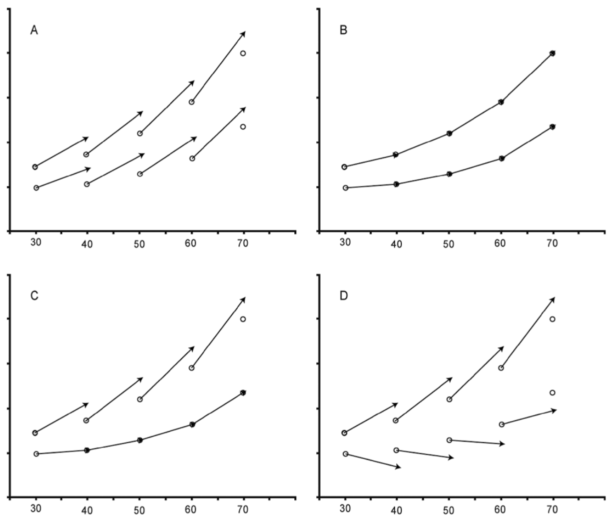
Hypothetical Aging Vectors and the Trend Function

An accelerated longitudinal design was developed to reveal aging patterns in certain developmental life stages, such as childhood, aggregating the overlapped trajectories of multiple birth cohorts (Miyazaki & Raudenbush, 2000). Bell (1953) originally developed the idea of linking together the changes observed for multiple cohorts. Within this approach, a lack of significant differences in the mean values of an outcome between cohorts at overlapped ages is called *convergence*. The convergence between cohorts is not always guaranteed. For some topics, we might find different age-specific levels of a given outcome between cohorts, and the intercohort trend itself might be an important research topic. For example, in this study, I am interested in assessing potential intercohort trends in the relationship between education and health rather than revealing aging or life-course patterns in the relationship between education and health (Kim & Durden, 2007).

In this study, vectors (linear approximations of the changes in an outcome over follow-up time in a panel study) are used to effectively provide a graphical means by which we may evaluate intercohort trends in health or other outcomes (McArdle, Ferrer-Caja, Hamagami, & Woodcock, 2002). In addition, this study utilizes a statistical method called the *trend function* to test the convergence or the absence of cohort trends: If the convergence is rejected, it suggests that there is a significant trend for a certain age group. The trend function is an equation that describes the difference between the changes over time (vector slope) and the slope of the cross-sectional age curve in the mid-follow-up year in an outcome (Mirowsky & Kim, 2007). If the trend function is significantly different from zero, the convergence is rejected, as described in detail in the Analytic Model section.

Figure 1 illustrates four hypothetical sets of aging vectors. The vectors represent the predicted values of physical impairment for 1-year age groups

Figure 1
Physical Impairment by Educational Status: Four Hypothetical Sets of Aging Vectors for a 10-Year Follow-Up Period



Note: *X*-axes represent age, and *y*-axes represent predicted physical impairment. The vectors in the lower portion of each graph display the functional health trajectories of college graduates, and the vectors in the upper portion display the trajectories of those with less than a high school diploma.

or birth cohorts from a hypothetical 10-year panel study. To simplify presentation, the graphs show only every 10th vector. Each graph shows the differences between two educational groups in aging vectors. The *y*-axes of the graphs represent predicted physical impairment, the *x*-axes represent age, and the two groups in the graphs represent college graduates (the lower vectors) and persons with less than a high school degree (the higher vectors).

In Panel A, small circles indicate the level of physical impairment at baseline for each age–education group, and the arrowheads indicate the level of physical impairment at the end of the follow-up period. As evidenced by the arrowheads above the circles at all ages, there are unfavorable trends in physical impairment for all of the age–education groups. As an example, compare the levels of physical impairment between the cohort that is age 40 at baseline (indicated by the circle) and the cohort at age 40 at the end of the survey (indicated by the arrowhead) among the college graduate group, located in the lower side of Panel A. The more recent 10-year cohort demonstrates a higher age-specific level of physical impairment at the same age, as indicated by the arrowhead that is above the circle at age 40. This pattern implies an unfavorable trend for college graduates of age 40. In this example, the direction of the trend effect is the same for all of the age–education groups: an equivalent unfavorable trend for all of the groups (the arrowheads are above the circles at the same distance). Therefore, an education-based difference in functional health does not increase or decrease due to the trends. This case implies that the absolute level of the current population's functional health will continue to decline in the future if the current trend disfavoring all of the age–education groups is sustained.

The aging vectors are generated from the two between-person equations of the linear growth-curve model, the constant and change equations for physical impairment (e.g., Equations 2 and 3 in the Analytic Model section). The constant of an outcome can be predicted at any point of follow-up (e.g., at baseline, mid-follow-up, or the end of follow-up). The models in this study are used to predict the constant at mid-follow-up, and the constant equation can provide a cross-sectional age curve in the mid-follow-up year. For example, in Panel A, imagine a curve connecting the midpoints of the arrows for each education group, which is a cross-sectional age curve for college graduates or the less educated.

In general, we can expect corresponding patterns between a cross-sectional age curve and aging vectors because the cross-sectional age curve reflects the age effect as well as the cohort effect. Panel B shows an example of perfect conformity (i.e., uniform convergence) between cross-sectional curves and aging vectors. The cross-sectional curves overlap precisely with the aging vectors. There is no trend (i.e., no cohort or period effects), so for the same age, there is no difference in health levels between the two 10-year-interval birth cohorts or 10-year interval periods. If we find this type of conformity, we can be confident that the health trajectories are the result of the aging process, and in this case, the age effect is disentangled from cohort and period effects (Miyazaki & Raudenbush, 2000). In this case of perfect conformity, the vector slope is equal to the slope of the cross-sectional curve at age at mid-follow-up (i.e., midpoint cross-sectional slope). In this case, the trend function has a zero value, statistically confirming no trend.

One advantageous characteristic of this synthetic cohort design is that it can provide a composite image of long-term life-course patterns with relatively short-term panel data. As shown in Panel B, the connected aging vectors provide an image of health trajectories across all adulthood that is solely due to the aging process, and the pattern is curvilinear in shape. All the age cohorts within each educational group follow the same curvilinear health trajectory across all adulthood. For other cases, except for the perfect conformity observed in Panel B, we cannot know the exact life-course trajectories across all adulthood because of the confounding of age, cohort, and period effects.

In Panel C, the intercohort trend is different across education groups. The less educated have an unfavorable trend, but there is no trend in functional health for college graduates. This case suggests that an education-based difference in functional health increases due to the trends because only the less educated group gets worse in functional health.

In Panel D, the trend disfavors the less educated and favors college graduates. The trend suggests that the education-based difference in functional health increases rapidly because the less educated group gets worse as the better educated group gets better.

Research Questions

In this study, I examine the intercohort trend in the relationship between education and two important health outcomes: physical impairment and depressive symptomatology. This study is intended to answer three specific questions: (a) Are there intercohort trends favoring or disfavoring certain educational groups for each health outcome? (b) Are the trends for physical impairment different from those for depressive symptomatology? (c) Are the trends different across age groups within each educational group?

Method

Sample

Data are from the Americans' Changing Lives (ACL) survey, a longitudinal data set based on a nationally representative sample of noninstitutionalized 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% oversamples of Blacks and those older than age 60. As recommended by the ACL study team, all analyses are adjusted by the final centered post-stratification weight, which takes into account nonresponse as well as the sample design. The weighted sample maintains the original sample size and corresponds to the July 1986 Bureau of the Census population estimates by sex, age, and geographic region.

This study utilizes three waves of data collected in 1986, 1989, and 1994. The three waves of ACL data can be classified into four exclusive groups by follow-up status. The first group is composed of the 2,348 respondents (65%) who participated in all three waves. The second group represents 519 respondents (14%) who participated in the first and the second surveys. The third group is composed of 214 respondents (6%) who participated in the first and the third surveys, and the fourth group represents 536 respondents (15%) who participated in the first wave only. Using a missing data imputation method, the latent growth model (LGM) estimated in this study includes all four groups.

Missing Data Treatments

This study uses an effective correction method for sample attrition: multiple model-based imputation (MMBI) with expectation maximization (EM) algorithms (Little & Rubin, 2002). The MMBI-EM method, which is implemented in EQS, Version 6.1, assumes that the absence of values is the result of a combination of tendencies predictable from the observed values as well as random chance. To assess the influence of sample attrition due to mortality on the results, additional analyses were conducted. An indicator for mortality was added to the constant and change equations of the LGM for each health outcome. Controlling for attrition due to death did not make any substantial difference in the main results (analyses available by request).

Measures

Physical impairment measures. Two functional health measures are examined as indicators of physical impairment. The multi-indicator LGM uses each measure as a subscale for a latent factor of physical impairment. The first subscale is Functional Impairment: *most severe level* (4), respondents who are currently confined to a bed or chair, have a lot of difficulty bathing, or cannot bathe; *moderately severe* (3), respondents who have a lot of difficulty climbing stairs, cannot climb stairs, have a lot of difficulty walking, or cannot walk but who are not in the previously defined level; *least severe level* (2), respondents who have a lot of difficulty doing heavy housework or cannot do heavy housework but who are not in the two previously defined levels; and *no functional impairment* (1), respondents answered no to all of the functional impairment questions. For the second subscale, Activity Limitation, respondents were asked to evaluate how much their daily activities are limited in any way by their health or health-related problems: *a great deal* (5), *quite a bit* (4), *some* (3), *a little* (2), or *not at all* (1). Cronbach's α for these two subscales is .798. The two subscales have skewed distributions. In the case of data that are not normally distributed, EQS 6.1 provides an option that corrects the χ^2 and standard errors for nonnormality in its maximum likelihood estimation (Yuan & Bentler, 2000). The model for physical impairment utilizes this correction method.

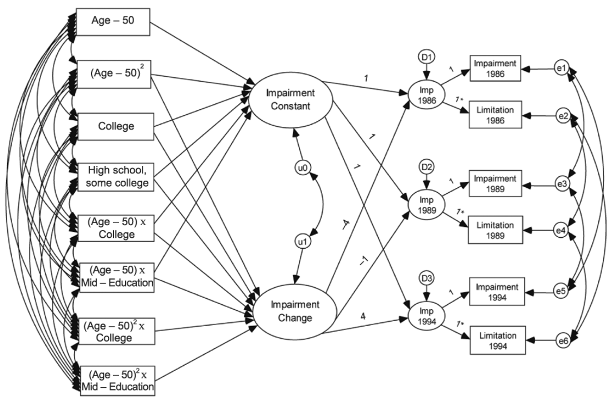
Depressive symptomatology measures. Depressive symptomatology is measured with seven items from the Center for Epidemiological Studies' Depression Scale (Radloff, 1977). Respondents were asked to evaluate how frequently in the past week they (a) felt depressed, (b) felt sad, (c) felt lonely, (d) had restless sleep, (e) had a poor appetite, (f) felt that everything was an effort, and (g) felt they could not get going. Items are coded from 1 to 3, with higher scores indicating greater frequency: *hardly ever* (1), *some of the time* (2), and *most of the time* (3). The multi-indicator LGM groups the items into two subscales: Sadness is the mean response to Items a, b, and c, and (b) malaise is the mean response to Items d, e, f, and g. Cronbach's α for these two subscales is .739.

Independent variables. Education is represented by two dummy variables composed of respondents who are college graduates (20% for weighted sample) and those who are high school (but not college) graduates (55% for weighted sample), with those who did not complete high school (25% for weighted sample) serving as the reference group. Age at mid follow-up (in 1990) is modeled as the deviation from age 50, which is a value close to the mean age in the sample. This centering method is conducted to reduce multicollinearity.

Analytic Model

Because the relationship between age and functional or mental health might be quadratic and we need to accurately estimate the relationship between age, education, and health in the LGMs in order to accurately examine the cohort trend, age-squared terms and their interactions with

Figure 2
Optimal Latent Growth-Curve Model for Physical Impairment Over 8 Years by Educational Attainment



Note: This multi-indicator latent growth model allows correlation of measurement errors across time. The indicators named "Impairment" represent the functional impairment measure, and the indicators named "Limitation" represent the activity limitation measure.

education should be assessed in models. However, including all the age-related terms in the LGM makes the model very complicated. Therefore, a stepwise procedure was used to identify the best fitting age and age–education interaction terms for each health outcome. The best fitting subset was found by comparing the results of stepwise forward inclusion to those of stepwise backward elimination. The two procedures identified the same model as the best fitting subset. The equations for the best fitting LGM for physical impairment are presented below.

The LGM in this study consists of three sets of equations: a within-person equation, between-person structural equations, and measurement equations (Mirowsky & Ross, 2007). Figure 2 illustrates the best fitting model. The factor loading to the functional impairment measure in each year is fixed to 1, which sets the metric of the physical impairment latent factor to that of the functional impairment measure. Certain constraints were imposed in order to generate a more parsimonious model. I set the factor loadings to activity limitation, intercepts of activity limitation, and correlations of measurement errors to have equal values over time.

Equation 1 describes the within-person equation, in which the health outcome Y for person i at time t is a linear function of time (–4, −1, and 4 in this study; time is centered on mid-follow-up) plus an error term e_{it} that is random with respect to time:

$$Y_{it} = a_{i0} + a_{i1}t + e_{it}. \tag{1}$$

Equations 2 and 3 describe the between-person structural equations to predict both the constant and change in physical impairment over a follow-up period. The within-person coefficients of Equation 1 are functions of age at mid-follow-up (A_{i0}) centered on a reference age (k, 50 in this study), educational attainment (C = 1 for college graduates and 0 for others; H = 1 for high school graduates and 0 for others), the interactions of age and education, and individual random deviations u_{i0} and u_{i1} from the expected constant and change with respect to time:

$$\begin{aligned} a_{i0} = b_{00} + b_{01}(A_{i0} - k) + b_{02}(A_{i0} - k)^2 + b_{03}C + b_{04}H \\ + b_{05}(A_{i0} - k)C + b_{06}(A_{i0} - k)H + u_{i0}; \end{aligned} \tag{2}$$

$$\begin{aligned} a_{i1} = b_{10} + b_{11}(A_{i0} - k)^2 + b_{12}C + b_{13}H + b_{14}(A_{i0} - k)C \\ + b_{15}(A_{i0} - k)H + b_{16}(A_{i0} - k)^2C + b_{17}(A_{i0} - k)^2H + u_{i1}. \end{aligned} \tag{3}$$

The following equations define the trend function T_i in terms of Equations 1 through 3.

$$T_i = \hat{a}_{i1} - \frac{d\hat{a}_{i0}}{dA_{i0}} \tag{4}$$

The trend function is defined in Equation 4 as the difference between vector slope and cross-sectional slope at age at mid-follow-up. In my model,

$$\begin{aligned} T_i &= b_{10} + b_{11}(A_{i0} - k)^2 + b_{12}C + b_{13}H + b_{14}(A_{i0} - k)C + b_{15}(A_{i0} - k)H \\ &\quad + b_{16}(A_{i0} - k)^2C + b_{17}(A_{i0} - k)^2H - \{b_{01} + 2b_{02}(A_{i0} - k) + b_{05}C + b_{06}H\} \\ &= [b_{10} + b_{12}C + b_{13}H - b_{01} - b_{05}C - b_{06}H] \\ &\quad + [b_{14}C + b_{15}H - 2b_{02}](A_{i0} - k) + [b_{11} + b_{16}C + b_{17}H](A_{i0} - k)^2. \end{aligned} \tag{5}$$

The perfect conformity or uniform convergence illustrated in Panel B of Figure 1 requires that the trend function is not statistically different from 0 at any age. Equation 5 shows that perfect conformity requires two things: The trend's constant is 0 ($b_{10} + b_{12}C + b_{13}H - b_{01} - b_{05}C - b_{06}H = 0$), and the trend is constant with respect to age ($b_{14}C + b_{15}H - 2b_{02} = 0$ and b_{11} +

$b_{16}C + b_{17}H = 0$). The present study examines the trends for each of three education groups. For college graduates ($C = 1$ and $H = 0$), the requirements for perfect conformity are $b_{10} + b_{12} - b_{01} - b_{05} = 0$, $b_{14} - 2b_{02} = 0$, and $b_{11} + b_{16} = 0$. For the group of high school graduates ($C = 0$ and $H = 1$), the requirements for perfect conformity are $b_{10} + b_{13} - b_{01} - b_{06} = 0$, $b_{15} - 2b_{02} = 0$, and $b_{11} + b_{17} = 0$. For the group with less than a high school diploma ($C = 0$ and $H = 0$), the requirements for perfect conformity are $b_{10} - b_{01} = 0$, $-2b_{02} = 0$, and $b_{11} = 0$. Utilizing EQS 6.1, a structural equation modeling program, I add each constraint (the requirement for perfect conformity) to an original LGM. If the increase of the χ^2 value when adding each constraint is significant at the .05 level, the requirement is not satisfied; thus, the perfect conformity is rejected.

Results

Physical Impairment

Table 1 presents the results from the best fitting LGMs for physical impairment and depressive symptomatology. The first LGM estimates the effect of education on physical impairment, and the second LGM estimates its effect on depressive symptomatology. The metric of the physical impairment latent factor is the same as that of the Functional Impairment scale, and the depressive symptomatology latent factor has the same metric as the Sadness scale. The table notes include information about model fit. For the two models presented in this study, the model fits are reasonably good (Bentler, 2003).

In the results of Model 1, the first two coefficients in column 1 represent the relationship between age at mid-follow-up and the constant of physical impairment at mid-follow-up. This model includes the interaction terms between age and education, and the reference group in education is those with less than a high school degree. Therefore, the first two coefficients in column 1 represent a cross-sectional age curve for those with less than a high school degree. The significant effect of age squared (.303) suggests that the cross-sectional curve is not linear. The third and the fourth coefficients in column 1 represent the effect of education on physical impairment at mid-follow-up. The reference age group is those aged 50 at mid-follow-up. Therefore, the third coefficient (–.346) represents the difference in physical impairment at mid-follow-up between college graduates and the least educated within the group of age 50. The fifth and sixth coefficients in column 1 indicate the significant interaction between age and education

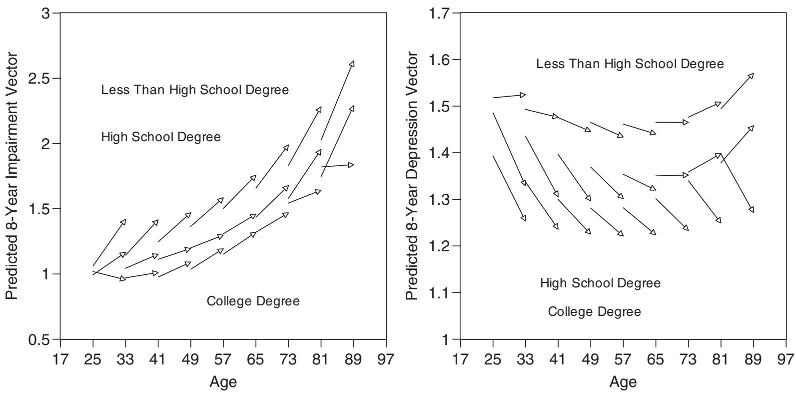
Table 1
Constant and Change of Physical Impairment (Model 1) and Depressive Symptomatology (Model 2) Regressed on Age at Mid Follow-Up, Educational Attainment, and Their Interactions

	Model 1[a]		Model 2[b]	
Variables	Constant	Change	Constant	Change
$(\text{Age} - 50)10^{-1}$	.152***		–.012***	
	(.013)		(.003)	
$(\text{Age} - 50)^2 10^{-3}$	.303***	.040***	.100***	.011***
	(.043)	(.007)	(.015)	(.003)
College degree[c]	–.346***	–.009	–.198***	–.004
	(.030)	(.006)	(.013)	(.003)
High school to any college[c]	–.217***	–.016**	–.114***	–.006**
	(.029)	(.006)	(.010)	(.002)
$(\text{Age} - 50)10^{-1} \times$ College[c]	–.044*	.006**		.002†
	(.019)	(.002)		(.001)
$(\text{Age} - 50)10^{-1} \times$ Mid-Education[c]	–.027†	.003†		.005***
	(.014)	(.001)		(.001)
$(\text{Age} - 50)^2 10^{-3} \times$ College[c]		–.070***		–.023**
		(.016)		(.007)
$(\text{Age} - 50)^2 10^{-3} \times$ Mid-Education[c]		–.002		–.009†
		(.011)		(.005)
Intercept	1.426***	.027***	1.452***	–.004*
	(.029)	(.005)	(.010)	(.002)
Residual variance	.191***	.001***	.045***	.00002
	(.012)	(.000)	(.002)	(.000)
Residual correlation	–.018		–.224	
R^2	.388	.180	.106	.731

Note: $N = 3{,}617$. Multi-indicator latent growth models with time centered on mid-follow-up are used with missing data imputed by expectation maximization. Metric coefficients have robust standard errors for nonnormal data in Model 1 and standard errors in Model 2.
a. Fit indexes: $\chi^2 = 187.06$, $df = 42$, $p < .001$; comparative fit index (CFI) = .996, standardized root mean square residual (SRMR) = .011, root mean square error of approximation (RMSEA) = .023; Yuan–Bentler scaled $\chi^2 = 153.54$, $df = 42$, $p < .001$.
b. Fit indexes: $\chi^2 = 120.90$, $df = 44$, $p < .001$; CFI = 1.000, SRMR = .011, RMSEA = .008.
c. Compared to those with less than a high school degree.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$. All tests are two-tailed.

in the constant of physical impairment. The difference in the constant of physical impairment between education groups increases with advancing age (diverging cross-sectional curves), as indicated by the negative values of the interaction coefficients.

Figure 3
Predicted 8-Year Aging Vectors of Physical Impairment and Depressive Symptomatology by Educational Attainment



In the results in column 2 of Table 1, the second and third coefficients represent the effects of education on change of physical impairment at age 50. The negative values of the coefficients indicate that the more educated have less increase in physical impairment over time than the least educated. The other coefficients in column 2 are difficult to accurately interpret, due to the quadratic relationships that exist between age and change in physical impairment. These complicated relationships are best interpreted graphically.

The graphs shown in Figure 3 provide summaries of the LGM results presented in Table 1. Each arrow (vector) represents the predicted origin and change in physical impairment or depressive symptomatology for a 1-year age group. To simplify the figure, vectors are shown for every eighth age group. A series of vectors in the lower portion of the graph on the left side of Figure 3 shows the functional health trajectories of college graduates, the vectors in the middle portion show those of high school graduates, and the vectors in the upper portion show those of the least educated. As expected from the results in Table 1, the less educated have higher levels of physical impairment and steeper increases in physical impairment over time for most age groups, compared to those with more education.

Intercohort trends appear to exist, as shown in the graph on the left of Figure 3. The graph illustrates unfavorable trends for those with less than a high school degree across all age groups: The 8-year newer cohorts have higher age-specific levels of physical impairment at all age groups. For instance, the 8-year newer cohort demonstrates a higher age-specific level of physical impairment at age 33, implying an unfavorable trend for the age group. Across all age groups, there are unfavorable trends for those with less than a high school degree (the arrowheads are above the origins at all ages). Similarly, slightly unfavorable trends appear to exist for high school graduates.

In the case of college graduates, no substantial intercohort trend (i.e., no cohort or period effect) is observed for most age groups: The 8-year newer cohorts have the same age-specific levels of physical impairment at most age groups. Therefore, the connected aging vectors for the college graduates illustrate the trajectory of physical impairment across the entire adulthood that is attributable to the aging process. The aging process reflects life-course experiences for the current population, organized by the contemporary social structure in the United States as well as universal biological processes. In support of the hypothesis that an educational difference in functional health increases in more recent cohorts, I observe differences in intercohort trends across levels of education such that the less educated demonstrate greater unfavorable trends in functional health.

Although we can assess intercohort trends by the graphs, we need to statistically test whether the trends are significant or not, using the trend function. The current study has an interest in the trend in functional health for each of three education groups. First, for those with less than a high school degree, the graph on the left of Figure 3 demonstrates an unfavorable trend for all age groups. For the group, Equation 5 and the results in Model 1 of Table 1 provide the values of the trend function for each age group:

$$\begin{aligned} T_i &= [b_{10} - b_{01}10^{-1}] + [-2b_{02}10^{-3}](A_{i0} - k) + [b_{11}10^{-3}](A_{i0} - k)^2 \\ &= [.027 - .152 \times 10^{-1}] + [-2 \times .303 \times 10^{-3}](A_{i0} - 50) + [.040 \times 10^{-3}](A_{i0} - 50)^2 \\ &= .012 - .0006(A_{i0} - 50) + .00004(A_{i0} - 50)^2. \end{aligned} \tag{6}$$

In Equation 6, the trend function for the least educated has positive values for all age groups in the sample, suggesting unfavorable trends. If the trend function has a positive value, the vector slope is more positive or less negative than the mid-period cross-sectional slope, implying that newer cohorts have higher age-specific values than older cohorts. The magnitude of the difference measures the speed of the trend.

To test whether the values in the trend function for the least educated are significantly different from 0, several restrictions were added to Model 1 of Table 1: The first restriction was $b_{10} - b_{01} \times 10^{-1} = 0$; the second and third restrictions were $-2b_{02} \times 10^{-3} = 0$ and $b_{11} \times 10^{-3} = 0$ (the age variables in the models were multiplied by a factor of either 10^{-1} or 10^{-3} in order to change the position of the decimal point within the coefficients). Adding the first restriction to the model increases the χ^2 by 6.6, which corresponds to $p < .05$, and implies that the unfavorable trend exists for the group aged 50 at midpoint. Therefore, the hypothesis of perfect conformity is rejected because both the first and second requirements need to be satisfied to confirm the uniform convergence. Adding the second and third restrictions to the model increases the χ^2 by 70.3, which corresponds to $p < .05$, and implies that the trend is not constant with respect to age: The trends differ across age groups. In the least educated, the trends are more unfavorable for younger and for older adults than for middle-aged adults, as shown in the left-hand graph in Figure 3, in which the arrowheads are above the origins with different distances across ages.

Second, for high school (but not college) graduates,

$$
\begin{aligned}
T_i = {} & [b_{10} + b_{13} - b_{01}10^{-1} - b_{06}10^{-1}] + [b_{15}10^{-1} - 2b_{02}10^{-3}](A_{i0} - k) \\
& + [b_{11}10^{-3} + b_{17}10^{-3}](A_{i0} - k)^2 = [.027 - .016 - .152 \times 10^{-1} \\
& + .027 \times 10^{-1}] + [.003 \times 10^{-1} - 2 \times .303 \times 10^{-3}](A_{i0} - 50) \\
& + [.040 \times 10^{-3} - .002 \times 10^{-3}](A_{i0} - 50)^2 \\
= {} & -.0015 - .00031(A_{i0} - 50) + .00004(A_{i0} - 50)^2. \qquad (7)
\end{aligned}
$$

Adding the first restriction ($b_{10} + b_{13} - b_{01} \times 10^{-1} - b_{06} \times 10^{-1} = 0$) to the model increases the χ^2 by 0.3, which corresponds to $p > .05$. Therefore, the trend is not significant for the group aged 50 at midpoint. Adding the second and third restrictions, $b_{15} \times 10^{-1} - 2b_{02} \times 10^{-3} = 0$ and $b_{11} \times 10^{-3} + b_{17} \times 10^{-3} = 0$, to the model increases the χ^2 by 16.8, which corresponds to $p < .05$, and suggests that the trends are different across age groups. Therefore, I reject the hypothesis of perfect conformity or uniform convergence. There are unfavorable trends for younger or older adults and little trends for middle-aged adults in the high school graduates, as shown in the left graph of Figure 3.

Finally, for college graduates, adding the first restriction ($b_{10} + b_{12} - b_{01} \times 10^{-1} - b_{05} \times 10^{-1} = 0$) to the model increases the χ^2 by 1.9, which corresponds to $p > .05$, and adding the second and third restrictions, $b_{14} \times 10^{-1} - 2b_{02} \times 10^{-3} = 0$ and $b_{11} \times 10^{-3} + b_{16} \times 10^{-3} = 0$, to the model increases the χ^2 by 3.2, which corresponds to $p > .05$. Therefore, both the first and second requirements for uniform convergence are satisfied, and I cannot reject the hypothesis of perfect conformity. As expected from the graph on the left of

Figure 3, in which aging vectors are mostly overlapped with the cross-sectional curve, there is no significant trend in physical impairment for college graduates.

Depressive Symptomatology

The LGM results for depressive symptomatology are presented in columns 3 and 4 of Table 1. The best fitting model for depressive symptomatology is different from that for physical impairment. The first and second coefficients in the top of column 3 represent the relationship between age and the depression constant at mid-follow-up for those with less than a high school degree. The negative effect of the age variable and the positive effect of the age-squared variable suggest a U-shaped cross-sectional curve in depressive symptomatology. The third and fourth coefficients (–.198 and –.114) in column 3 represent the difference in the depression constant between college graduates or the mid-educated and the least educated. No interaction between age and education exists. Therefore, the difference in the depression constant between education groups does not change with age. In the results in column 4 of Table 1, the second and third coefficients represent the effects of education on change of depression at age 50. The other coefficients in column 4 are difficult to accurately interpret, due to the quadratic relationships that exist between age and change in depression. These complicated relationships are best interpreted graphically.

The right-hand graph in Figure 3 provides summaries of the Model 2 results presented in Table 1. College graduates (the lowest vectors in the graph) show lower initial levels of depression and lower depression change regardless of age group, compared to the group with less than a high school diploma. This graph also demonstrates that college graduates enjoyed favorable intercohort trends in all age groups (the arrowheads are below the origins at all ages). For high school graduates, there are intercohort trends favoring them in most age groups, but the trend diminishes in older age groups and disappears in very old age groups, as illustrated in the right-hand graph of Figure 3. This graph also indicates relatively weak trends favoring those who did not complete high school, but the favorable trends appear to exist only for certain age groups.

In sum, the better educated enjoyed more favorable trends than the least educated. This implies that the educational disparity in mental health relatively increased due to the trends, corroborating previous findings that indicate a stronger effect of education on health or mortality in more recent cohorts.

With the same procedure followed for physical impairment, I test the hypothesis of perfect conformity in depressive symptomatology for each of three education groups, using the trend function. To test whether the trend function is zero regardless of age for the least educated, I add several restrictions to Model 2 of Table 1. When the first restriction is added to the model, the χ^2 change is negligible, suggesting that the trend is not significant for the group aged 50. Adding the second and third restrictions to the model increases the χ^2 by 23.6, which corresponds to $p < .05$. Therefore, the trends are different across age groups in the least educated, and the hypothesis of uniform convergence is rejected.

For high school graduates, adding the first restriction to the model increases the χ^2 by 30.8, which corresponds to $p < .05$, and leads to the rejection of the hypothesis of perfect conformity. Adding the second and third restrictions to the model increases the χ^2 by 12.8, which corresponds to $p < .05$, suggesting that there are significant variations in the trends across age groups. Finally, for college graduates, adding the first restriction to the model increases the χ^2 by 5.1, which corresponds to $p < .05$, again leading to the rejection of the hypothesis of perfect conformity. When the second and third restrictions are added to the model, the χ^2 change is negligible. This suggests that there is no significant variation in the trends across age groups, which is also expected from the graph on the right of Figure 3: The arrowheads are above the circles with a similar distance at all ages for college graduates.

Discussion

First, the results indicate that intercohort trends are unfavorable to less educated persons in functional health, and little or no trend is found for college graduates. This study also finds intercohort trends to be favorable to more educated persons in mental health. These results suggest that the education-based disparity in health is greater in more recent cohorts; for example, the mental health of college graduates improved whereas the functional health of those with less than a high school diploma got worse. These results extend the findings of previous research suggesting that the effect of education on self-rated health and mortality has grown in more recent cohorts and provide a richer understanding of the trends than previous studies by presenting results for each educational subgroup. If this contemporary trend is sustained, we can expect worsening health inequality by educational status.

Second, the trends are different for physical impairment versus depressive symptomatology, even though the trends imply increasing education-based disparities in both health outcomes. For physical impairment, the disparity increased because the less educated worsened. For depressive symptomatology, the disparity increased because the more educated improved. These results argue for the necessity of examining trends in education and health using diverse health outcomes so as to identify differences in the trends and any dimensions of health in which urgent social interventions are needed, thereby preventing worsening health among the less educated.

Third, the trends are different across age groups within certain educational groups. In the least educated, the trends for physical impairment are more unfavorable for younger and older adults than for middle-aged adults. Similar patterns are found among high school graduates. Less educated younger and older adults suffer more from the trends than less educated middle-aged adults. For depressive symptomatology, there are intercohort trends favoring high school graduates through early old age, but the trends diminish and then disappear in older ages. Less educated older adults do not enjoy mental health benefits via these trends, while the less educated in other age groups enjoyed certain benefits. In summary, less educated younger and older adults appeared to experience more disadvantages and fewer advantages with respect to health between 1986 and 1994.

Why Is the Effect of Education on Health Stronger in More Recent Cohorts?

Many previous studies have suggested an epidemiological transition to chronic disease from infectious disease as an explanation for the increasing disparity in health between education groups (Feldman et al., 1989; Lynch, 2003). When chronic disease emerged as a major health problem in the 1960s, the initial SES gap in health was small because the methods of prevention or remedy for chronic disease were not fully developed and diffused (Omran, 1977). As the developed methods of prevention or remedy for chronic disease have rapidly diffused to better educated groups, the education-based health disparity has increased (Lynch, 2006). The better educated have greater financial capacity to get the latest medical treatment with advanced technology for certain chronic disease than the less educated. Moreover, the better educated have a higher sense of control, and better life conditions allow them to adopt preventive lifestyles against certain chronic diseases in cases where lifestyle is uncovered as important for health (Mirowsky & Ross, 2003; Pappas et al., 1993).

Increasing structural inequality might explain the stronger effect of education on health in more recent cohorts through the increasing effects of educational credentials on inequalities in occupation, income, and access to health care (Lynch, 2003; Singh & Siahpush, 2006). According to Williams and Collins (1995), the widening health disparity is related to rising economic inequality since the mid-1970s along with increasing differences in health care quality and accessibility between SES groups. According to Lynch (2006), the greater effect of education on self-rated health in more recent cohorts can mainly be explained by the mediating role of income. Two mechanisms were operating through income to generate the intercohort trend: One is the increasing economic return of education in more recent cohorts or periods, and the other is an increasing effect of income on health in more recent cohorts or periods. In the changing labor market conditions over several recent decades, educational attainment has become increasingly important for one's income. Moreover, income may have become increasingly important to health because the cost of health care has increased substantially. In other words, the more educated within recent cohorts may have enjoyed better economic returns than did the more educated within earlier cohorts. At the same time, the less educated within recent cohorts may have suffered from less accessibility to quality health care compared to the less educated within earlier cohorts.

The increasing human capital (e.g., psychosocial resources) derived from education might also explain the increasing importance of education for health in more recent cohorts (Mirowsky & Ross, 2007), although the results of Lynch's study do not support this explanation. The better educated within recent cohorts may be both more knowledgeable and proactive in maintaining or improving their health compared to the better educated within earlier cohorts. As a result of epidemiological transition, the effect of managing a healthy lifestyle on health may be increasing, and education plays an essential role in health behaviors and lifestyle. The better educated have greater social networks, a higher sense of control, and stronger motivation to enhance their health, and these psychosocial resources may have more importance for health in the current period, when chronic diseases predominate (Koskinen, 2003).

Implications and Limitations

This study provides evidence that the education-based disparity in health is increasing, but there appear to be variations in the trend depending on health outcomes. Previous studies have focused on mortality; thus, variations in the trend across diverse dimensions of health outcomes are unclear. In the present study, the trends in depressive symptomatology favor more educated persons, but the trend in physical impairment does not favor more educated persons. There are relatively weak trends in depressive symptomatology favoring middle-aged adults who did not complete high school, and the trends in physical impairment disfavor them. These results provide a theoretical implication that the trends related to the education-based health disparity might differ by various health outcomes. Additionally, to confirm a health outcome on which the less educated suffer from an unfavorable trend provides a policy implication for effective social interventions (giving priority to the health outcome, which is physical impairment in this study) to prevent worsening health among this group. Another policy implication of the results of this study pertains to the identification of more vulnerable or disadvantaged age groups as target populations for social intervention. Less educated younger and older adults appear to suffer more from the trends in health than less educated middle-aged adults.

To examine other major health outcomes, such as morbidity and cognitive functioning, with available panel data represents a proper direction of future research in this topic. Another direction for future research is to differentiate the stages of health problems in the study of education and health. According to a study by Herd, Goesling, and House (2007), the effect of education on onset of functional limitation was significant, but its effect on progression of functional limitation, given the onset, was not significant. The findings of Herd and colleagues suggest the importance of the distinction between onset and progression of a health problem for more refined understandings of education and health.

Why, then, are the education-based cohort trends different between functional and mental health? The unfavorable trend in functional health for the least educated may be associated with the trend that medical care accessibility and quality declined for the least educated due to increasing health care costs (Lynch, 2006). College graduates may not be affected by increasing health care costs in utilizing quality medical care because they are more able to afford such costs. The favorable mental health trend for the better educated may be related to the fact that the economic and stock market boom from the mid-1980s to 2000 benefited the better educated in terms of income and wealth (House et al., 2005). Additionally, as technology advances, the effectiveness and market value of a college degree may rise, resulting in greater economic return for the more educated in the labor market (Mirowsky & Ross, 2007). The improved financial conditions for the better educated may bring about better overall conditions of life and lower depression. However, the economic boom and advances of technology may not benefit those without a high school degree because of increasing educational requirements in the labor market. The less educated might constantly experience a low sense of hope for their future career and economic security, keeping their level of depression constantly high.

A potential limitation related to period effects warrants further consideration: the potential sensitivity to the survey period due to the utilization of relatively short-term panel data. A relatively short survey period might not adequately represent contemporary cohort trends. However, if additional studies using data from different periods are conducted and yield similar patterns of results, potential period sensitivity can be ruled out as a significant limitation.

The intercohort trends disfavoring the less educated in physical impairment and favoring the better educated in depressive symptomatology, indicated by the graphs with aging vectors and tested in the trend function, provide further evidence that the education-based disparity in health is greater in more recent cohorts or periods.

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