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Depression and the Sense of Control: Aging Vectors, Trajectories and Trends*

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Abstract

Adulthood trajectories of outcomes such as depression and the sense of control measure aspects of the human condition that Americans may view as objects of change. Social science should provide information on that progress, or its absence. Whether these trajectories change their shape, and how and why if they do, is important theoretically too. A range of birth cohorts coexist in time, place, and social relationship. Each cohort, as it goes through adulthood, follows in aggregate a path left by older ones, reshaping that path as it goes. The shapes of the trajectories, and the trends reshaping them, represent two *inseparable* aspects of the same phenomenon. This report describes methods for mapping aging trajectories and inter-cohort trends, using linear latent-growth models of relatively brief followup data (six years in the examples). It reviews shared research ideals that led to the model: put theory into modeling, go where the data lead, use what you have, go beyond where you have been, and risk being precisely wrong.

Keywords

accelerated longitudinal design; growth curves; structural equation models; age-period-cohort; trajectories and trends; aging vectors; trend function; synthetic and virtual cohort models; depression; sense of control

It takes awhile to realize the obvious; even longer to work out the implications. About a decade ago I started thinking about something I've known since graduate school in the 1970s. As each birth cohort goes through life its average level of an outcome, such as depression or the sense of control, follows a more-or-less smooth curve that I call an aging trajectory. As each birth cohort follows earlier ones through life, the shape of an aging trajectory may change, which I call a trend. If a trend exists in the shape of an aging trajectory, then followup studies find that the changes as a birth cohort goes from one age to another (say, from age 18 to age 24) do not match the differences between people of those two ages in a given year of the study. Aging researchers have long known that trends across birth cohorts in age-specific outcomes produce that divergence. As I thought about this, I realized a fascinating implication. The departure of followup changes in an outcome from cross-sectional differences in it measures the trends. Given that measure, it might be

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possible to “de-trend” the aging trajectories and, more importantly, show how those trajectories are changing across cohorts (Mirowsky and Kim 2007).

This paper summarizes aging-vector analysis and the trend-function method for sketching the shapes of aging trajectories and the changes in them across cohorts. Before defining those terms and detailing the procedures, though, it reviews how I became absorbed in these matters. When I was told that I would receive the 2012 Leonard I. Pearlin Award I saw it as an opportunity as well as an honor. The award carries the name of a scientist whose research provided a foundation and inspiration for my own. In addition, it is given by the Mental Health Section of the American Sociological Association. Members of the section form a community of scientists with shared interests and ideals. The Pearlin Award gave me an opportunity to think about how those ideals have shaped my work and led to my current interests. It also gave me a chance to share my enthusiasm with this community. Nothing pleases me more than this chance to engage other members of the community in aging-vector analysis. I got to these interests by following five communal ideals that provide the main headings below. First, *put theory into modeling*, as illustrated by research relating depression to the sense of control. Second, third and fourth, go where the data lead, use what you have, and go beyond where you have been, as illustrated by efforts to map the aging trajectory of depression. Fifth and finally, *risk being precisely wrong*, as illustrated by an aging-vector analysis of trends in the adulthood trajectory of the sense of control.

Put Theory into Modeling

Theory in modeling tries to define a set of elementary concepts that together have complex, but testable, implications. Research on the consolation-prize theory of alienation provides a good example of the analytic process, carried out over several decades by many theorists and researchers. In sociology, the consolation-prize theory of alienation was developed to explain the lower aspirations and commitment of lower-status workers at the time. Merton (1946) theorized that a belief in luck, chance and fate helps people to preserve their self-esteem in the face of failure, but also discourages sustained effort to advance socially and economically. Analyzing data from surveys conducted in 1942–1949, Hyman (1966) found that lower-status respondents placed less emphasis on college as essential to advancement, preferred a secure job with low income over an insecure job with high income, and were less likely to believe that hard work could get them a promotion or that the quality, energy and willingness of one's work are important for advancement. Hyman saw this as “a *self-imposed* barrier to an improved position” (p. 448). He speculated that “this value system arises out of a realistic appraisal of reality and in turn softens for the individual the impact of low status” (1966, p. 488). Similar ideas could be found in cultural anthropology and social-psychological studies of political and economic development (Mirowsky and Ross 1990a).

The consolation-prize theory of alienation held sway in sociology, political science and anthropology throughout the 1950s, '60's and 70's. Toward the end of that period, in the 1970's, sociologists were increasingly developing mental health studies using anonymous interviews, structured questionnaires, quantitative indexes, and random samples representative of entire cities, states, and the nation. Most studies of that period focused on disruptive and distressing life events. Some of those studies led the investigators to question the consolation-prize theory. Do alienation and fatalism ease the emotional impact of low status and failure? Again and again, the answer was clear. *No*. Quite the opposite. 1980: Wheaton finds that fatalism does not reduce distress net of socioeconomic status, but instead mediates the correlation between distress and low status. 1981: Pearlin, Lieberman, Menaghan and Mullan find that disruptive job events increase economic strain, decrease feelings of mastery and self-esteem, and thereby increase depression. 1983: Turner and Noh find that, among Ontario women who had recently given birth, those with a low sense of

control are *more* distressed by the combination of low status with undesirable events or low emotional support. 1984: Krause and Stryker find that fatalistic beliefs increase the association between stressors and psychological distress. 1984: Mirowsky and Ross find no difference between Anglos and Mexicans or Mexican Americans in the effect of fatalism on depression and anxiety, despite much higher levels of fatalism among persons of Mexican heritage. 1986: Kluegel and Smith find that low-income Americans who say their own positions are due to effort and ability have more positive emotions and fewer negative ones than the low-status persons who say their positions are due to luck or other things.

How could the theorists and researchers of the 1940s, '50s and '60s have been so wrong? Null hypothesis: They missed something big. Perhaps they were not as insightful and observant as supposed. Alternative hypothesis: they missed something elementary — one or more simple ideas of a set that, when combined, have large and complex implications. Clue Number 1: Wheaton's optimum and the threshold of dysfunction.

Empirical failure of the consolation-prize theory turned ideas around 180 degrees. Now theory saw an illusory sense of control as comforting false consciousness among lower status Americans. Problem: If lower-status persons have the most need for an illusory sense of control, why do they have a lower sense of control? Why don't they increase their sense of control until they feel just fine? Why doesn't everyone? Because, Wheaton (1985) argued, at some point a higher sense of control becomes ineffective. Well-being does not float free of experience. The emotional benefits of a sense of control result largely from effective action. Effectiveness balances optimistic motivation against unrealistic appraisal. As the sense of control increases, the incremental benefits from greater optimism diminish and the incremental costs of unrealistic appraisal rise. The two forces cancel at the threshold of dysfunction, which defines the optimum sense of control.

Wheaton's ideas and model provided the critical breakthroughs. The sense of control, and its emotional benefits, are anchored in reality. A parabolic curve represents the trade-offs between optimism and realism. His results show a large but limited benefit to optimism, with the threshold of dysfunction at .827 standard deviations above the mean. That puts the optimum at the 80th percentile. Those below (roughly 4 of 5) would benefit emotionally from a higher sense of control. (The optimum can be considerably higher in younger samples. Using a 1992-94 U.S. sample aged 15 through 54, Kielcolt, Hughes and Kieth (2009) found an estimated optimum with a Z-score corresponding to the 97th percentile, which was above the survey index's top code).

Wheaton's ideas and model embodied two of the elementary concepts relating distress to the sense of control: optimism and realism. The unified model of instrumental realism (Mirowsky and Ross 1990a) added a third element: power. Realistic for a high-income, college-educated non-Hispanic white differs considerably from realistic for a low-income, high school dropout minority. In the unified model, the sense of control predicted from measures of socioeconomic status represents power. The model has five equations with three elementary definitions:

$$\begin{aligned}
\hat{D} &= k_0 - k_1 E \\
E &= P + O + R \\
P &= \hat{C} \\
O &= g_1 (C - \hat{C}) \\
R &= -g_2 (C - \hat{C})^2 \\
\therefore \\
\hat{D} &= k_0 - k_1 \hat{C} - k_1 g_1 (C - \hat{C}) + k_1 g_2 (C - \hat{C})^2
\end{aligned} \tag{1}$$

In the model, effectiveness (E) decreases depression (D) linearly. Power (P), optimism (O) and realism (R) add up to effectiveness. The sense of control predicted from socioeconomic status equals power. The deviation from expected sense of control, times a constant, equals optimism. (In our best estimates, correcting for measurement error, $g_1 \approx .1$). Squared deviations from the expected sense of control, times a negative constant ($-g_2 \approx -.2$), equal realism, which is maximized when the deviation is zero. Expected depression reaches its minimum when the negative realism slope cancels the positive optimism slope, which is when the deviation from expected sense of control equals $(1/2)(g_1/g_2)$. If optimism had no effect then g_1 would be zero and the optimum sense of control would equal its predicted value. Instead, optimism's effectiveness keeps the ideal sense of control above the most realistic one (at about the 81st percentile of deviation from predicted value).

Putting the elements together implies several things, seen in Figure 1. Higher status increases the optimum sense of control and decreases the level of depression expected at the optimum. At all levels of the sense of control, higher status makes an additional increase in sense of control more beneficial (or less detrimental). (Here and later, the *sense of control* is measured with the Mirowsky-Ross 2x2 index (Mirowsky and Ross 1991; Wolinsky et al., 2004). Possible scores range from -2 to +2, although real scores rarely fall below -1).

Clearly, the consolation-prize theory of alienation remains as wrong as ever. Figure 1 gives no reason to think that a lower sense of control benefits those for whom it is more realistic. (See also, Mirowsky and Ross 1990a,b 1991, Mirowsky, Ross and Van Willigen 1996). Even so, it shows how insightful theorists and observant researchers could have been so wrong. The psychological impact of a higher sense of control uniformly benefits more those with greater real social power. The lower the status, the lower the optimum, and the worse the lowest expected distress. Theoretically, this may explain why lower status persons have a lower sense of control, even though it gives them no consolation.

The unified model of instrumental realism combines three simple elements, abstracting them from vague but resonant themes of realistic yet counterproductive alienation and illusory yet beneficial sense of control. Combined, the elements have complex implications showing precisely how the old ideas were wrong yet reasonable and potentially coherent though seemingly contradictory. Those are goals of putting theory into modeling.

Go Where the Data Lead

No data analysis ever turns out exactly as expected. Unexpected finding mark trails into the unknown. In our theorizing about the optimum sense of control, Catherine Ross and I thought of its predicted value as a shared component of belief formed by experiences common to those of similar status. The model defined power as synonymous with the sense of control predicted from socioeconomic status, indicated by income, education and minority status. That all made sense, and generally worked out well, except for one

unexpected result. Age had an unignorable large, nonlinear effect on the sense of control. Had the curve been parabolic, peaking around age 55, we would have thought that age was acting as a stand-in for wealth or the like. Instead, the best-fitting function was a cubic curve with its origin at the beginning of adulthood: $-c (Age - 18)^3$. The curve is nearly flat in early adulthood through middle age, but the slope becomes increasingly negative at a slowly accelerating rate, yielding an increasingly steep drop-off in old age. This looked like something different from the rise and fall of power and influence over the adult lifetime.

The accelerating old-age decline in sense of control implied a corresponding increase in old-age depression. That got us thinking about the adulthood trajectory of depression. Prior to 1990, no studies compared levels of depression across the full range of adulthood ages (Mirowsky and Ross 1992). Most studies either looked at young adults getting through school and into the work force, or adults of prime working and parenting ages, or adults in or entering retirement, treating them as distinct populations. A review of 27 studies comparing retirement-aged adults to samples of other ages found that six reported the older adults were more depressed, eight reported they were less depressed, and 13 found no difference or mixed results, leading the author to call depression in old age a “scientific myth” (Feinson 1985). However, a meta-analysis of studies regressing depression on years of age found that it decreased with age in studies of young and middle-aged adults but increased with age in studies of seniors (Newmann 1989). That suggested a roughly u-shaped relationship with depression rising in old age, perhaps because of declining sense of control. To confirm the basic pattern we compared mean depression scores across 10-year age groups in our 1985 Illinois survey, our 1990 U.S. survey of adults ages 18 and up, and (later) the 1988-89 National Survey of Families and Households (Mirowsky and Ross 1992, Mirowsky 1996). In all three, bar graphs showed a big drop between early adulthood and middle-age, low levels through late middle age, and rising levels in old age.

Use What You Have

Followup data would have allowed us to see how depression levels change as cohorts go from one age to another. We didn't have that kind of data, but we did have our 1990 national U.S. survey designed to study work and family correlates of depression (Mirowsky and Ross 1992). We began by reviewing the theoretical concepts of age. We found five views: age as maturity, decline, stage in the life cycle, survival, and place in historical trends. Each of these suggested a distinct set of mediators relevant to one or both ends of the curve. For example, higher levels of education across cohorts were a major 20th Century trend. Depression is less frequent at higher levels of education, so some of what appears to be an old-age increase in depression might actually result from lower education in older cohorts. Employment status, marital status and household income represent the life-cycle of adulthood social statuses that favor middle-aged well-being. Physical dysfunction and low sense of control represent old-age decline, likely contributing to rising old-age depression. Women have higher levels of depression than men, and live longer, perhaps creating a survival bias.

Next we specified a model for progressive adjustment (Mirowsky and Ross 1992; Mirowsky 2012). We wanted a model that could isolate mediators predominating at different parts of adulthood, with the best fit for the fewest parameters. Our component-curve model, shown in equation 2, has three core elements, illustrated in Figure 2.

$$\hat{D} = a_0 + a_1 \ln(Age - 17) + a_2(Age - 18)^3 + \sum_{j=3}^k a_j (X_{ij} - \bar{X}_j) \quad (2)$$

In the model, a_0 represents the depression predicted at age 18, the beginning of adulthood, because the two age functions equal zero at that age. The component $a_1 \ln(Age-17)$ represents the rapid decline in depression in early adulthood (assuming $a_1 < 0$). The slope of the function is steepest at age 18 and gets flatter rapidly as age increases. The component $a_2 (Age-18)^3$ represents the rising depression predominating in late adulthood (assuming $a_2 > 0$). The slope of the function is flat in early adulthood but gets steeper at an accelerating rate, mirroring the sense of control curve found earlier. The final component represents adjustment for confounders (survival factors) and mediators. By centering them on their sample means (or proportions), the intercept represents the depression predicted at age 18 given mean values on the adjusted variables. Figure 2 shows the unadjusted component curves and their sum.

Progressive adjustment shows substantial components of the curve attributable to trends in education, the life-cycle of work, family and economic status, and old-age decline, as illustrated in Figure 3. Model 3 adjusts for sex and minority status. Model 4 adds adjustment for education. Were it not for the lower-than-average education of seniors, they would have noticeably lower depression. Even so, the rising component remains highly significant and the general pattern remains u-shaped. Model 5 adds adjustment for employment and marital status, considerably flattening the age trajectory. The coefficients a_1 and a_2 both become insignificant. Model 6 adds adjustment for economic status, flattening the component curves even more. Model 7 adds the control and dysfunction adjustments, inverting the cubic coefficient. The predicted value at age 18 changes little until those final adjustments. Were it not for those mediators, young adults would be notably more depressed and old adults would be notably less depressed. As a whole, the cross-sectional analysis implies that depression does fall and then rise in adulthood, chiefly following the cycle of employment, marital and economic statuses. It also rises increasingly in old age because of rising dysfunction and declining sense of control.

Go Beyond Where You Have Been

Theoretically-driven cross-sectional models and analyses made a lot of progress. Even so, the possibility remained that actual changes as persons aged would deviate substantially from the cross-sectional age curves. In 1991 we started to design a 3-wave followup survey of Aging, Status and the Sense of Control (ASOC), with interviews three years apart for a total period of six years. We estimated that, with about 2,500 persons in the baseline interview, we would have enough cases at the end and enough time passed to measure the age-specific changes. We submitted our grant application to the National Institute on Aging, with the earliest possible time line of 1995 through 2001 for data collection, and several years after for final data analysis. That gave us a long wait for the data, and even longer for the answers. In the meantime, we needed to find existing data that would allow us to prototype some of the models and analyses. The National Survey of Families and Households (NSFH) had about 13,000 respondents ages 18 and older interviewed in 1988-89, with 76.1% interviewed again six years later in 1994-95 (Sweet and Bumpass 1990). It did not measure the sense of control, but it had the same measure of depression we planned to use. That gave us a solid basis for working out the models we could run in our data after 2001.

The second wave of NSFH data became available about the same time as data from the first wave of our ASOC survey, so we were developing the prototype change models while analyzing ASOC's baseline data. As soon as John Reynolds and I started analyzing the 2-wave NSFH data, we knew that attrition needed to be addressed (Mirowsky and Reynolds 2000). The effect of baseline depression on the probability of dropping out of the study increased with the cube of age (centered on 18).

Figure 4 shows my first attempt at a graph integrating cross-sectional and followup results. The circles represent unadjusted age-specific means at baseline for persons who dropped out. The straight lines represent unadjusted age-specific means at baseline and at followup, and thus the mean changes, for persons who stayed in at wave 2. The two curves represent the baseline cross-sectional component-curve model (equation 2 above) estimated separately in the two groups. Clearly, the baseline differences in depression between those who later dropped out and those who stayed in were increasing with age. Interaction models showed no significant difference in the coefficient of the logarithmic falling component, but a significant one in that of the cubic rising component. The difference remained significant with adjustment for sex, minority status, education, impairment and subjective health. The adjustments for education, impairment and subjective health reduced the coefficient of the rising component to zero for those who remained in the sample, but not for the dropouts.

This looked like trouble. What could we do about it? If baseline depression interacted with age-related decline to discourage followup participation, then adverse changes in depression probably did too. We can't just limit followup modeling to those who remain in the sample. The cross-sectional analyses of baseline differences by followup status implied that doing so would grossly underestimate the old-age increases in depression. How could we estimate the unobserved changes of those who dropped out? John Reynolds noted that this problem looked similar in form to one in econometrics: estimating the reservation wage, the lowest wage rate at which a worker would take a particular type of job. The wages earned by those who took the job are observed, but not the wages that would have been earned by those who did not take it.

Our tolerance model followed a standard reservation-wage format (Mirowsky and Reynolds 2000; Reynolds 2005 (details and code)). Here's the idea. The model has two latent equations. One regresses changes in the outcome on a set of independent variables. The other regresses tolerance for those changes on the same set of variables. Tolerance is a threshold. If depression increases beyond the individual's tolerable level, the person drops out. If not, the person stays in. The probability of remaining in the sample equals the probability that the increase in depression stays below the threshold. The effect of a variable on the probability of remaining in the sample is proportional to the difference between its effect on change in depression and its effect on the threshold for tolerable increases. Working backward from the simultaneous regressions of attrition and observed changes in depression allows estimation of the latent tolerance and change equations.

Each variable in the model can affect change and tolerance to different degrees (Mirowsky and Reynolds 2000, Table 3, page 499). For example, in our model education lowers the predicted increase in depression but raises the tolerable increase. This suppresses the beneficial effect of education on observed changes in depression. Race/ethnicity works the same way. White Anglos have more favorable predicted changes in depression than others, but a much higher tolerance for increases. That suppresses the observed followup divergence in depression. Likewise for the logarithmic component of the age curve, which predominates in early adulthood. It predicts advantageous decreases in depression, but also raises tolerance for increases. That suppresses observed improvements in early adulthood. Females have larger predicted increases in depression than males, but even greater tolerance for

increases. This magnifies the apparent effect of being female on observed increases in depression. Subjective health reduces predicted increases in depression, and somewhat lowers the threshold, slightly magnifying the apparent impact.

Figure 5 shows the predicted change in depression and tolerance threshold by age, assuming good subjective health and no physical impairment at baseline. (Calculations, alternative baseline values, and other graphs are in a spreadsheet available on request). According to the model, depression increases steeply in old age. However, the increase in depression that takes a person out of the sample diminishes dramatically in old age. As a result, the increases predicted for those who stay in the sample rise only to about age 69, and then diminish. The gap between the reconstructed and observable changes represents the bias introduced by age-based differences in tolerance for increases in depression.

The tolerance model presented itself as a way of measuring and correcting attrition bias. On consideration, it revealed itself as something more. It measures a new and interesting psychosocial factor: tolerance for adverse changes. In a mental health model, a low tolerance threshold suggests social vulnerability or detachment. That idea opens new vistas and leads to new questions. How would social support affect tolerance? Trust? Wealth? Neighborhood disorder? What happens if we change the outcome to anxiety, mistrust, fear of victimization, subjective health, physical impairment, income, employment, economic hardship, marital status? Does each input tend to move tolerance for adverse changes in all outputs in more or less the same direction? Is there something like a latent factor influencing tolerance for adverse changes across a wide range of outcomes? If so, where did it come from? Do predicted adverse changes and tolerance for them usually move in opposite directions, suppressing the observed detrimental changes? Do predicted beneficial changes and tolerance usually move together, closing a participation gap?: What began as the technical problem of attrition opened a path into the previously unseen. Survey dropouts used to be vexing. Now they can be a resource for discovery. Theory in modeling reveals fresh outlooks that can turn trouble into opportunity.

Before moving on, think back to those early literature reviews comparing depression across age groups. Were the researchers who called old-age depression “a scientific myth” wrong? Yes. Were their measurements and statistical analyses flawed? Probably not, especially given the methods of the day. Were they wrong to have spoken so bluntly? Should they have obscured their conclusions in jargon and equivocation? No. The unambiguous statement raised the issue, sending many researchers to their data sets, developing and estimating models, following the results, using what they had and then going beyond. Now, decades later, we see quite clearly how someone insightful and observant could have been so wrong back then. Had they been more circumspect, we might not have learned as much as quickly. That brings us to the final ideal.

Risk Being Precisely Wrong

Sometimes analysts balk at following a model to its logical conclusions, fearing over-interpretation. They should not. Science advances faster when precisely wrong than when vaguely right. When they are right, precise predictions make progress. When they are wrong they make progress possible. We can't know how the predictions will fare in the long run. Right or wrong, though, will become clear only to the extent that the predictions are precise.

The sense of control's adulthood trajectory provides an especially good example, for one memorable reason. I had it *seriously* wrong for nearly twenty years. Think back to the earlier sections on putting theory into modeling and going where the data lead. Catherine Ross and I got into aging research because our cross-sectional models showed a major effect of age on

the sense of control. The shape of the curve seemed to rule out age operating as a measure of socioeconomic status, which follows a parabolic rise and fall peaking around age 55. Four separate cross-sectional surveys taken in 1985, 1990 and 1995 (two surveys) all showed something else: high and largely constant sense of control at the beginning of adulthood through middle age, followed by an increasingly steep decline in old age (Mirowsky 1995, 1997, Ross and Mirowsky 1992, 2002)(For the old age decline, see also Wolinsky and Stump 1996; Wolinsky et al. 2003).

Based on the cross-sectional models, I thought that the sense of control increases in school, and stops increasing on leaving school. Small early-adulthood increases vanished with adjustment for education. In addition, high-school followup data showed increases in sense of control for those who stayed in school but not for those who dropped out (Lewis, Ross and Mirowsky 1999). Overall, the pattern suggested that people leave school with a sense of control that remains more or less constant until eroded by the losses of old age (chiefly impairment, poor health, and shortening time horizons). That “more-or-less constant” part, from age 18 into the 50s, looked quite different from the parabolic arc of socioeconomic status.

Built up in school, used up in old age. That’s what I thought. The ASOC followup data put that elegant notion in the bin. The changes confirmed the old-age decline, but dramatically altered the early-adulthood picture (Mirowsky and Ross 2007). The changes showed steep increases in the sense of control at the beginning of adulthood, gradually flattening out until becoming old-age declines after age 60. Furthermore, the early-adulthood and middle-age increases occurred for those with high school or college degrees even if they did not get additional schooling over the period.

How did I get it so wrong? Back to basics. I wasn’t so much wrong, as missing something elementary. The cross-sectional models lacked a critical element: trends, the changes across cohorts in the adulthood trajectory. A sharp and prolonged trend toward higher sense of control in early adulthood had been flattening the cross-sectional age curves in early adulthood. Within cohorts, the sense of control was rising sharply as they entered middle age, but newer cohorts were beginning adulthood with a higher sense of control, closer to that of the cohorts already in middle age. As a result, the cross-sectional differences in early adulthood were much flatter than the followup increases, masking the parabolic form of the trajectory.

Now, step back and take a critical view of what that last paragraph claims. A charmingly neat idea provides a plausible explanation for unexpected inconsistencies. Other than that, what makes us think it is true? How do we know that newer cohorts were entering adulthood with a higher sense of control? What makes us think that the trajectory within cohorts follows a parabolic curve? It took some work to get that clear.

In Search of a Model

With followup data in hand, we needed a precise way to map the aging trajectories using the changes as cohorts went from one age to another. Clearly, it needed to distinguish the shape of an adulthood trajectory within cohorts from the trends changing the trajectory across cohorts.

At first the aging-versus-cohort question seems like a technical detail — an analytic problem with methodological solutions. On reflection, the relation between aging trajectories and inter-cohort trends becomes a central issue in itself, for two reasons. The first arises from humanist values and social science’s role in measuring social progress. Trajectories of outcomes such as depression and the sense of control measure aspects of the human

condition that Americans may view as objects of change. Social science should provide information on that progress, or its absence.

The second arises from a purely scientific goal of understanding for its own sake. Whether these trajectories change their shape, and how and why if they do, is important in itself. A range of birth cohorts coexist in time, place, and social relationship. Each cohort, as it goes through adulthood, follows a path left by older cohorts, reshaping that path as it goes. The shapes of the trajectories, and the trends reshaping them, represent two *inseparable* aspects of the same phenomenon.

The tolerance model of the previous section provided new insights and information, but shared a limitation with the earlier cross-sectional models. The estimated effects confound age as place in the life cycle with age as place in history. Implicitly, the tolerance models assume there is no trend across cohorts in the age-specific changes in the outcome. Someone may yet work out how to map an aging trajectory and its trends in a tolerance model. In the meantime, latent-growth models provided some handy tools for seeing and measuring the trends and sketching the changing trajectories. Newer estimation techniques correct much (but not all) of the attrition bias revealed by the tolerance model, as summarized later. They allow estimation of the aging vector models from which aging-vector graphs and virtual cohort curves are derived, as described later. Before getting to that, though, I want to describe a detour on the way to those models.

The model that failed

Those familiar with developmental psychology's accelerated longitudinal designs typically think of aging trajectories in a particular way. The developmental model has a long history and large literature that I will not go into here. I was familiar with that literature and initially turned to it for a modeling approach. For me, using the three-wave ASOC data, the developmental model consistently mired in estimation problems: failure to converge, negative variance estimates, non-invertible matrices and the like. Other sociologists using other data sets have had better luck with the developmental model. Fine. It did not work for me. Thinking about why not and what to do instead lead me to what I call the aging-vector approach.

The developmental approach invariably begins with the assumption that individuals follow inherent, personal aging trajectories. In modeling terms, the shape of an aging trajectory must be specified within individuals. The assumption has two implications: the within-person equation must be a function of age at the time of observation (A_{it}) rather than of the time of observation (t), and the within-person equation must represent the shape of the hypothesized trajectory. A parabolic trajectory requires an age-squared term within-person, and a cubic trajectory additionally requires an age-cubed term within person, as in the following equation for person i :

$$Y_{it} = a_{0i} + a_{1i}A_{it} + a_{2i}A_{it}^2 + a_{3i}A_{it}^3 + e_{it} \quad (3)$$

The inherent-curve assumption produces many technical problems in studies of adults, because it typically takes many data points over decades to reliably map the shape of an individual's personal adulthood trajectory. The alternative approach avoids those problems by coding the shape of the trajectory in the between-person model, as shown later.

The alternative approach also rests on a different view of how the aging trajectories take shape and change across birth cohorts. The developmental view sees the aggregate trajectory as merely averaging across random individual deviations in universal, inherent

developmental curves. The alternative view sees individuals as embedded within cohorts that follow the paths of previous cohorts, perhaps altering those paths in passing. Personal values of an outcome deviate randomly with respect to the collective trajectory. The shape of a trajectory could be purely conventional and external to the individual, or a mix of conventional and developmental forces.

The inherent-curve model often encounters problems addressing trends across birth cohorts. The obvious way to model the trends is to predict each of the a coefficients from the year of birth. That implies an interaction between year of birth and each age term (linear, squared, and cubed). The interactions often produce the equivalent of a multicollinearity problem. Two common solutions may get the model to run, but lose or obscure much of the trend information. One approach limits the effect of birth year to the intercept term, avoiding the implied interactions with age. This assumes that the shape of the trajectory is the same across cohorts, differing only by level. In other words, it treats the trend as the same at every age. The results are traditional synthetic-cohort curves having the same age profile in all cohorts. Another approach treats birth cohort as a higher-order sampling unit, analogous to a sample of schools with students within them. Implicitly, this treats the differences across cohorts as random. It ignores the sequential order of cohorts, and obscures the direction and speed of the age-specific trends across them.

Together, those practical and theoretical observations led me to seek an alternative way to find the shapes of aging trajectories and the trends in those shapes across cohorts.

Dynamic expectations

To begin with, some concepts and terms should be clarified. An *aging-trajectory* is an outcome's within-cohort predicted value described as a function of age. An *inter-cohort trend* is the direction and speed of change across birth cohorts in one or more coefficients of the trajectory function. Changes in those coefficients imply changes across cohorts in age-specific values of the outcome. The speed and direction of inter-cohort trends may vary across ages.

Aging trajectories and cohort trends represent dynamic expected values toward which individual random deviations regress. Everyone who learns about either regression analysis or the logic of clinical trials learns about regression to the mean, in the bivariate case, or to the expected (predicted) value in the multivariate case. Trajectories and trends are moving expected values. They describe *nonrandom, directional* changes in expected values within and between cohorts along more or less smooth paths.

Sometimes random changes and drifts from year to year are called trends (as in stock prices), but not in aging vector analysis. Likewise, the word "period" commonly refers to an epoch or era characterized by a dominating and distinguishing condition or event, such as World War II or the Great Depression. Life course researchers sometimes speak of "period" effects as the impact on a cohort's trajectory of having crossed a particular segment of life during a specific historic interval. In aging vector analysis, historic alterations of trajectories are called trends. In aging vector analysis "period" refers to the years of the survey, and also the interval between the beginning and end. Period effects are survey-year residuals that may be serially correlated with each other but are uncorrelated with age and cohort.

Arrows in time: aging vectors and their graphs

My engineer father always says, "Keep it simple." Jinyoung Kim and I started with the simplest possible concept: arrows in time that we call *aging vectors* (Mirowsky and Kim

2007). An aging vector points from a cohort's age and predicted value at the beginning of a period to its age and predicted value at the end.

An *aging-vector graph* shows the vectors for the sequence of cohorts in the followup survey (Mirowsky and Kim 2007). An arrow (or line) represents the aging vector of each cohort. Figure 6 shows two aging-vector graphs of the sense of control that are consistent with the baseline cross-sectional curve. (The ASOC survey covered six years, so the arrows are six years long. For visual clarity, the graphs only show every sixth one-year cohort.)

Mathematically, there is no necessary correspondence between the changes within cohorts as they go from one age to another and the difference between two cohorts of those ages in a given year. *Empirically*, stability in the life course trajectory as one cohort follows another produces some level of conformity. The top panel of Figure 6 illustrates a perfect conformity, which has been called “convergence” or “linkage.” It shows a parabolic trajectory with no trend. For any given age, the prediction for the cohort reaching it at the end of the study equals the prediction for the one of that age at the beginning. The arrows line up head to tail. More importantly, the slope of each linear vector (each arrow) equals the cross-sectional slope. The absence of a substantial trend across 60 birth cohorts seems unlikely for most outcomes. It also may be unwelcome. Generally, the outcomes chosen for study are things that society would like to increase or decrease across cohorts.

The bottom panel of Figure 6 shows the actual results (Mirowsky and Ross 2007). The followup slopes go from positive to negative, consistent with a parabolic trajectory. The arrows point upward among the youngest adults but progressively flatten among the next oldest until they begin pointing progressively more downward. However, the aging vectors do not line up head to tail in early adulthood. Instead, each arrow ends above where the next one begins. The disjunction progressively diminishes until the arrows line up in old age. The upward slopes in early adulthood are steeper than the cross-sectional curve. Those differences between followup and cross-sectional *slopes* measure the trends. They indicate a steep trend toward higher sense of control at the beginning of adulthood that gradually diminishes until disappearing near the end of adulthood. Imperfect conformity such as this results when at least one parameter of the underlying trajectory's equation changes across cohorts.

What Our Aging Vectors Find

So far we have mapped the aging vectors of eight health and mental health outcomes. Although each has its own pattern, some generalizations seem worth noting.

Trends are the norm

Most of the outcomes tested show significant trends (Mirowsky and Ross 2010), including depression (Kim 2008; Mirowsky and Kim 2007, Ross and Mirowsky 2006), sense of control (Mirowsky and Ross 2007), mistrust (Mirowsky and Ross 2010), anger (Mirowsky and Schieman 2008), economic hardship (Mirowsky and Ross 2010), physical impairment (Kim 2008; Mirowsky and Ross 2005; Ross and Mirowsky 2010, 2011), subjective health (Mirowsky and Ross 2008), and body-mass index (BMI)(Mirowsky 2011).

Only anxiety shows no trend, contradicting the “era of anxiety” hypothesis (Mirowsky and Schieman 2008, Mirowsky and Ross 2010). (The absence of a trend in feelings of anxiety supports Horwitz and Wakefield's (2012) argument that the increasing prevalence of anxiety disorders is an epidemic of diagnosis).

Trends differ by age

None of the trends are constant with respect to age. The trends for sense of control, economic hardship, anger, mistrust, and BMI are fastest in early adulthood, in a desirable direction for the first four but an undesirable one for BMI. The trends for subjective health and physical impairment are fastest at the oldest ages, in an undesirable direction, particularly when holding education constant. Depression shows substantial trends at the beginning and end of adulthood, in a good direction at the beginning but a bad one near the end.

Cross-sectional age curves understate but rarely deceive

Critiques of cross-sectional age curves often warn they may overstate the aging trajectories. Our results imply the opposite. *All* of our measured trends flattened the cross-sectional curves, making them conservative estimates of the aging trajectories. Although all of the trajectories implied by the follow-up changes were steeper than the corresponding cross-sectional age curves, only one was *substantively* different: the sense of control trajectory.

Sketching Trajectories and Trends

Aging vector graphs provide a lot of information in compact form. They transform the inscrutable coefficients of linear latent growth models into a pattern readily grasped by the human eye and mind. Even so, they only suggest the profile of the aging trajectory. How can we actually sketch it? Traditional synthetic cohort curves use the slopes, but my virtual cohort curves use the trends.

Synthetic cohort curves: easy, common, and wrong

Synthetic-cohort curves string together the vector slopes. Figure 7 shows the synthetic-cohort curve for the youngest cohort, along with the aging-vectors (Mirowsky and Ross 2007). A synthetic cohort curve begins at the origin level of a reference cohort. From there it sequentially adds the subsequent age-specific slopes (changes). Graphically, it moves each vector line up until it connects with the preceding one. Mathematically, it integrates the age-specific slopes across midpoint ages. In this case it creates a parabolic curve that rises until around age 60 (when the arrow has a flat slope) and then declines.

A synthetic cohort curve represents the within-cohort trajectory *if there is no interaction between age and cohort*. The only trend allowed is in the level at every age. The synthetic cohort curve is exactly the same for every other cohort, simply shifted down to cross that cohort's aging-vector at its middle.

Does it make sense to assume that the trajectory is the same across cohorts, just higher in newer ones? That amounts to assuming that the trend across cohorts is the same at every age. The aging-vectors contradict it. They show a sizable upward trend at the beginning of adulthood that gradually disappears toward the end of it. The synthetic cohort curve in Figure 7 illustrates the distortion. It projects a very high sense of control for the youngest cohort when it reaches old age. That would require a very large trend toward higher sense of control in old age, but there was little or no trend in old age during the study.

Virtual cohort curves: tracing the trends

Virtual-cohort curves allow interactions between age and cohort. In Figure 7, the virtual cohort curve of the reference cohort bends back down toward the levels at midpoint observed for the oldest cohorts. It does so because there is little or no trend toward higher sense of control observed at those ages.

The virtual cohort models improve over synthetic cohort curves by allowing the age-specific slopes to change across cohorts. To do this, the exploratory model described here makes a simplifying assumption: a linear trend across cohorts in their age-specific expected values. Figure 8 shows the sense-of-control trajectories for three cohorts born at 24 year intervals. The vertical gap between adjacent cohorts is the same for all pairs at each age. However, the size of that gap changes across ages, in proportion to the difference between the followup slope and the slope of the cross-sectional level at mid followup. The model sketches the shape of the within-cohort trajectory adjusting for the trends, while illustrating the implications of the observed trends for changes in the level, location or shape of the trajectory.

The curves in Figure 8 imply several things. The sense of control follows a much steeper trajectory within cohorts than directly apparent from the vectors alone. The maximum sense of control is shifting upward across cohorts. The age of maximum sense of control is shifting downward, to younger ages. The age-specific declines in late adulthood are getting faster in newer cohorts. The age-specific increases in early adulthood are getting slower. Overall, the sense-of-control trajectory rises higher in newer cohorts, but peaks younger, and converges on the same low sense of control in old age as in earlier cohorts.

Figure 9 shows the virtual cohort curves for depression, using the aging vectors from Mirowsky and Kim (2007). (The model is parabolic rather than the log and cube component-curve model, so it oversimplifies to some extent). The graphs imply several things. The within-cohort trajectories are much steeper than cross-sectional curves or even traditional synthetic cohort curves. The trends greatly mask the impact of age on depression. The age of minimum depression is shifting downward, to younger ages, but the minimum expected depression is not changing much across cohorts. In early adulthood the level of depression is dropping but the decreases in depression with aging are getting slower. In old age the level of depression is rising and the increases in depression with aging are getting faster.

The virtual cohort curves for depression and the sense of control differ, but they have two things in common. Both show marked improvements in early adulthood but not in old age. As a result, both show a marked decrease in the optimum age.

The Trend-Function Method for Sketching Virtual Cohort Curves

This section illustrates the step-by-step method for measuring age-specific trends and deriving the virtual-cohort equations for graphs such as in Figures 7, 8 and 9. This is the method in a nutshell: measure the trends as the differences between followup and cross-sectional slopes, multiply the trend at each age by the number of years it will take a cohort to get to that age, and add those values to the cross-sectional levels.

Step 1: Specify a linear latent-growth model with time centered on mid followup. Equation 4 describes the within-person (level-1) model, in which the outcome Y for person i at time t is a linear function of time plus an error term e_{it} that is random with respect to time:

$$Y_{it} = a_i + b_i t + e_{it} \quad (4)$$

Time is the difference between an interview year and a reference year, which should be the midpoint of followup. Centering time on the first survey year creates bias that increases with the length of followup. The bias is usually small, but might as well be avoided.

Regress the within-person level and slope coefficients on polynomial functions of age at mid followup. For the sense of control, equations 5 and 6 describe the between-person (level-2)

model, where k is a reference age (21), and the residuals u_{ai} and u_{bi} may covary. (Procedures for backward elimination from a third-order polynomial trajectory with linear trends in all four coefficients are available on request).

Equation 5 predicts the within-person level at time zero ($\hat{Y}_{i0} = \hat{a}_i$). It is called the level, origin, or constant equation.

$$a_i = a_0 + a_1 (A_{i0} - k) + a_2 (A_{i0} - k)^2 + u_{ai} \quad (5)$$

Equation 6 predicts the within-person average change over the followup period ($\Delta \hat{Y} / \Delta t = \hat{b}_i$). It is called the change or slope equation.

$$b_i = b_0 + b_1 (A_{i0} - k) + u_{bi} \quad (6)$$

Step 2: Estimate the model with methods that use all the cases, such as *Full Information Maximum Likelihood* (FIML), *Multiple Imputation* (MI), or *Bayesian Estimation* (BE). They minimize distortion from the effects of baseline age and outcome on attrition. Never delete the cases with missing followup data.

Columns 1 and 2 of Table 1 give the coefficients of the level and slope equations respectively, using FIML estimation. All of the coefficients are significant at $p < .01$. The model fits the data quite well: CFI = 1.000, RMSEA = .007.

Step 3: Find the cross-sectional slopes by taking the first derivative of the level at midpoint with respect to age then, as in equation 7.

$$\partial \hat{a}_i / \partial (A_{i0} - k) = a_1 + 2a_2 (A_{i0} - k) \quad (7)$$

Column 3 of Table 1 shows the coefficients for the derivative. Notice that the coefficients describing the cross-sectional slopes do not equal those describing the followup slopes in column 2. This difference exists because of the trends. Were there no trends, the two sets of coefficients would be roughly the same, and not significantly different. (A spreadsheet illustrating and automating steps 3 through 7 is available on request).

Step 4: Compute the trend function by subtracting cross-sectional slopes from corresponding followup slopes. This measures the direction and rate of the inter-cohort trend at each age. Subtracting equation 7 from equation 6 produces the trend function.

$$T_i = (b_0 - a_1) + (b_1 - 2a_2) (A_{i0} - k) \quad (8)$$

The trend function's coefficients embody the effect of cohort on the coefficients of the life course trajectory. Technically, the trend function is the derivative of the outcome with respect to birth year, evaluated at the midpoint of the followup when $t = 0$.

Notice that the coefficients of the trend function represent constraints that can be added to a model to test for the significance of trends in specific coefficients of the trajectory. For example, adding the constraint $b_0 - a_1 = 0$ provides a χ^2 difference test of the null hypothesis that there is no trend at age k (Kim 2008; Mirowsky and Kim 2007).

The trend function also provides a formal definition of perfect conformity: $T_i = 0$ for all A_{i0} . Perfect conformity may be rare, but studies often may find a range of ages where T_i is near zero, as occurs at the oldest ages in this example.

To get the trend function for the sense of control, subtract the coefficients in column 3 of Table 1 from the corresponding coefficients in column 2. The result shows how the trajectory's coefficients are changing across cohorts. The absence of a quadratic term implies that there is no trend in the curvature of the parabolic trajectory. The positive intercept means that the level of the sense of control at age k is increasing in younger cohorts. The negative linear term means that the slope at age k is declining in younger cohorts. Taken together, the two coefficients imply that the trend toward higher sense of control gets less positive at older ages, reaching zero around age 91 (because setting $T_i = 0$ and solving for A_{i0} yields 91.3).

Step 5: Measure the total change in level predicted by the time the reference cohort reaches each age. Multiply each age-specific trend times the number of calendar years it will take the reference cohort to reach that age. The reference cohort is age k at midpoint, and any other cohort is age A_{i0} . So, it will take $A_{i0} - k$ years for the reference cohort to reach any other cohort's midpoint age. Thus, multiply the trend function times $(A_{i0} - k)$. As shown in column 5 of Table 1, the product simply shifts the trend function's coefficients up one polynomial order.

Step 6: Add the product $T_i (A_{i0} - k)$ to the age-specific level of the outcome at time zero. The resulting equation describes the level projected for the reference cohort when it reaches each age, as illustrated in Figure 10.

Summing the coefficients in columns 1 and 5 of Table 1 produces the coefficients for the virtual cohort trajectory of the reference cohort. Notice that the first two coefficients are simply the intercept terms of the level and slope equations. This is true for all models. It serves as a check on calculations.

Step 7: Compare the virtual cohort curves of multiple cohorts fixed years apart, as in Figure 8. The trend function provides a means of projecting the virtual cohort curves of other cohorts. If the other cohort is d years older than the reference cohort at time zero, then simply multiply $-d$ by the trend function and add the result:

$$\begin{aligned} V(k+d) &= \hat{a}_{i0} + T_i (A_{i0} - (k+d)) \\ &= \hat{a}_{i0} + T_i ((A_{i0} - k) - d) \\ &= [\hat{a}_{i0} + T_i (A_{i0} - k)] - dT_i \quad (9) \\ &= V(k) - dT_i \end{aligned}$$

For example, the cohort 45 years old at mid followup was 24 years beyond the age of 21 then. Thus, $V(45) = V(k) - 24T_i$. Likewise, $V(69) = V(k) - 48T_i$. These equations describe the two lower curves in Figure 8.

Step 8: Graph the curves.

That's it. The novel concepts and procedures might seem tricky at first. With a little practice they come to seem obvious. Just remember: measure the trends as the differences between followup and cross-sectional slopes, multiply the trend at each age by the number of years it will take the reference cohort to get there, and add those values to the cross-sectional levels.

Seeing Change

Aging-vector and virtual-cohort graphs provide new ways of visualizing and analyzing life course trajectories and their trends. As population measures cast in intuitive terms they should not be reified. Even so, it would be cowardly not to speculate about the trends behind the trends in depression and the sense of control. I see two major forces at work. On the good side, rising levels of education give newer cohorts ever greater real control over their own lives. This transforms adulthood work from self-denying drudgery to self-expressive creativity. On the bad side, the progressive displacement of human physical activity speeds the rise of impairment. Newer cohorts rely on ever more drugs taken over ever longer segments of life to manage the consequences of too much food and too little physical activity, compounding the problems. The good side predominates in early adulthood, but the bad side cancels those gains at earlier and earlier ages.

That is how it has been going lately. Will it continue to go that way? We won't know for a long time. The virtual cohort curves show us where aging trajectories are heading if the trends remain unchanged.

Pursue the Ideals

Now you understand why I say that it takes a while to realize the obvious, and even longer to work out the implications. Longer yet, I should add, to see how it all turns out. Science never knows where it will go. Pursuing the ideals creates insights yet to be imagined. Put theory into modeling. Go where the data lead. Use what you have. Go beyond where you have been. Risk being precisely wrong. No pursuit could be more engaging, challenging and satisfying.

References

- Feinson, Marjorie Chary. Aging and Mental Health. *Research on Aging*. 1985; 7:155–174. [PubMed: 3903893]
- Horwitz, Allan V.; Wakefield, Jerome C. *All We Have to Fear: Psychiatry's Transformation of Natural Anxieties into Mental Disorders*. Oxford University Press; New York: 2012.
- Hyman, Herbert H. The Value Systems of Different Classes: A Social Psychological Contribution to the Analysis of Stratification. In: Bendix, Reinhard; Lipset, Seymour Martin, editors. *Class, Status and Power: Social Stratification in Comparative Perspective*. 2nd ed.. Free Press; New York: 1966. p. 488-99.
- Kiecolt, K. Jill; Hughes, Michael; Keith, Verna M. Can a Sense of Control and John Henryism be Bad for Mental Health? *The Sociological Quarterly*. 2009; 50:93–714.
- Kim, Jinyoung. Intercohort Trends in the Relationship Between Education and Health. *Journal of Aging and Health*. 2008; 20:671–693. [PubMed: 18583482]
- Kluegel, James R.; Smith, Eliot R. *Beliefs About Inequality*. Aldine de Gruyter; New York: 1986.
- Krause, Neil; Stryker, Sheldon. Stress and Well-Being: The Buffering Role of Locus of Control Beliefs. *Social Science and Medicine*. 1984; 18:783–90. [PubMed: 6729538]
- Lewis, Susan K.; Ross, Catherine E.; Mirowsky, John. Establishing a Sense of Personal Control in the Transition to Adulthood. *Social Forces*. 1999; 77:1573–99.
- Merton, Robert K. *Mass Persuasion*. Harper; New York: 1946.
- Mirowsky, John. Age and the Sense of Control. *Social Psychology Quarterly*. 1995; 58:31–43.
- Mirowsky, John. Age and the Gender Gap in Depression. *Journal of Health and Social Behavior*. 1996; 37:362–380. [PubMed: 8997891]
- Mirowsky, John. Age, Subjective Life Expectancy, and the Sense of Control: The Horizon Hypothesis. *Journal of Gerontology: Social Sciences*. 1997; 52B:S125–34.
- Mirowsky, John. Cognitive Decline and the Default American Lifestyle. *Journal of Gerontology: Psychological Sciences*. Jul; 2011 66B(Supplement):i50–i58.

- Mirowsky, John. Analyzing Associations Between Social Circumstances and Mental Health. In: Aneshensel, Carol; Phelan, Jo; Bierman, Alex, editors. *Handbook on the Sociology of Mental Health*. 2nd Edition. Springer; New York: 2012. p. 143-165.
- Mirowsky, John; Kim, Jinyoung. Graphing Age Trajectories: Vector Graphs, Synthetic and Virtual Cohort Projections, and Cross-Sectional Profiles of Depression. *Sociological Methods and Research*. 2007; 35:497–541.
- Mirowsky, John; Reynolds, John R. Age, Depression and Attrition in the National Survey of Families and Households. *Sociological Methods and Research*. 2000; 28:476–504.
- Mirowsky, John; Ross, Catherine E. Mexican Culture and its Emotional Contradictions. *Journal of Health and Social Behavior*. 1984; 25:2–13. [PubMed: 6725922]
- Mirowsky, John; Ross, Catherine E. The Consolation Prize Theory of Alienation. *American Journal of Sociology*. 1990a; 95:1505–35.
- Mirowsky, John; Ross, Catherine E. Control or Defense? Depression and the Sense of Control Over Good and Bad Outcomes. *Journal of Health and Social Behavior*. 1990b; 31:71–86. [PubMed: 2313078]
- Mirowsky, John; Ross, Catherine E. Eliminating Defense and Agreement Bias from Measures of the Sense of Control: A 2×2 Index. *Social Psychology Quarterly*. 1991; 54:127–45.
- Mirowsky, John; Ross, Catherine E. Age and Depression. *Journal of Health and Social Behavior*. 1992; 33:187–205. [PubMed: 1401846]
- Mirowsky, John; Ross, Catherine E. Education, Cumulative Advantage and Health. *Aging International*. 2005; 30:27–62.
- Mirowsky, John; Ross, Catherine E. Life Course Trajectories of Perceived Control and their Relationship to Education. *American Journal of Sociology*. 2007; 112:1339–82.
- Mirowsky, John; Ross, Catherine E. Education and Self-Rated Health: Cumulative Advantage and its Rising Importance. *Research on Aging*. 2008; 30:93–122.
- Mirowsky, John; Ross, Catherine E. Emotional Well-Being Across the Life Course. In: Scheid, Teresa L.; Brown, Tony, editors. *Handbook for the Study of Mental Health: Social Contexts, Theories, and Systems*. 2nd Edition. Cambridge University Press; New York: 2010. p. 361-384.
- Mirowsky, John; Ross, Catherine E.; Van Willigen, Marieke. Instrumentalism in the Land of Opportunity: Socioeconomic Causes and Emotional Consequences. *Social Psychology Quarterly*. 1996; 59:322–37.
- Mirowsky, John; Schieman, Scott. Gender, Age, and the Trajectories and Trends of Anxiety and Anger. In: Turner, Heather A.; Schieman, Scott, editors. *Stress Processes across the Life Course: Advances in Life Course Research*. Vol. 13. 2008. p. 45-73.
- Newmann, Joy Perkins. Aging and Depression. *Psychology and Aging*. 1989; 4:150–65. [PubMed: 2675927]
- Pearlin, Leonard I.; Lieberman, Morton A.; Menaghan, Elizabeth G.; Mullan, Joseph T. The Stress Process. *Journal of Health and Social Behavior*. 1981; 22:337–356. [PubMed: 7320473]
- Reynolds, John R. RESWAGE: Stata Module to Estimate a Reservation Wage Model with Endogenous Selection. *Econpapers*. 2005 <http://econpapers.repec.org/software/bocbocode/s448901.htm>.
- Ross, Catherine E.; Mirowsky, John. Households, Employment, and the Sense of Control. *Social Psychology Quarterly*. 1992; 55:217–35.
- Ross, Catherine E.; Mirowsky, John. Age and the Gender Gap in the Sense of Personal Control. *Social Psychology Quarterly*. 2002; 65:125–45.
- Ross, Catherine E.; Mirowsky, John. Sex Differences in the Effect of Education on Depression: Resource Multiplication or Resource Substitution? *Social Science & Medicine*. 2006; 63:1400–13. [PubMed: 16644077]
- Ross, Catherine E.; Mirowsky, John. Gender and the Health Benefits of Education. *The Sociological Quarterly*. 2010; 51:1–19.
- Ross, Catherine E.; Mirowsky, John. The Interaction of Personal and Parental Education on Health. *Social Science and Medicine*. 2011; 72:591–599. [PubMed: 21227556]

- Sweet, James A.; Bumpass, Larry L. *American Families and Households*. Russel Sage; New York: 1990.
- Turner, R. Jay; Noh, Samuel. Class and Psychological Vulnerability Among Women: The Significance of Social Support and Personal Control. *Journal of Health and Social Behavior*. 1983; 24:2–15. [PubMed: 6853996]
- Wheaton, R. Blair The Sociogenesis of Psychological Disorder: An Attributional Theory. *Journal of Health and Social Behavior*. 1980; 21:100–124. [PubMed: 7391526]
- Wheaton, R. Blair Personal Resources and Mental Health: Can There Be Too Much of a Good Thing?. In: Greenley, James R., editor. *Research in Community and Mental Health*. JAI; Greenwich, Conn: 1985. p. 139-84.
- Wolinsky, Fredric D.; Stump, TE. Age and the Sense of Control Among Older Adults. *Journal of Gerontology: Psychological and Social Sciences*. 1996; 51:S217–20.
- Wolinsky, Fredric D.; Warwick, Kathleen W.; Babu, Ait N.; Cranch, Kurt; Tarn, William M. Age, Aging, and the Sense of Control Among Older Adults: A Longitudinal Reconsideration. *Journal of Gerontology: Social Sciences*. 2003; 4:S212–20.
- Wolinsky, Fredric D.; Warwick, Kathleen W.; Metz, Stacie M.; Babu, Ait N.; Tarn, William M.; Cranch, Kurt. Test-Retest Reliability of the Mirowsky-Ross 2×2 Index of the Sense of Control. *Psychological Reports*. 2004; 94:725–32. [PubMed: 15154208]

Figure 1.

Higher SES increases the optimum sense of control and decreases depression (days per symptom per week) at the optimum. For the graph, Low SES = 60-year-old minority with 10 years of education and \$10,000 household income (1984 dollars), High SES = 30-year-old non-minority with 18 years of education and \$50,000 household income. (Mirowsky and Ross 1990, data from the 1985 Illinois Survey of Well-Being, Catherine E. Ross P.I., funded by the Research Board of the University of Illinois).

Figure 2.

Falling and rising components of depression (days per symptom per week) by age (Mirowsky and Ross 1992, 1990 U.S. survey of Work, Family and Well-Being, Catherine E. Ross P.I., funded by National Science foundation grant number SES-8916154).

Figure 3.

Progressive adjustment of the component-curve model. (Predictors are centered on their means or proportions, Mirowsky and Ross 1992, 1990 U.S. survey of Work, Family and Well-Being).

Figure 4.

Depression (days per symptom per week) at baseline and changes over 6-years of follow-up, by age. (Mirowsky and Reynolds 2000, data from the U.S. National Survey of Families and Households, 1988-89 and 1994-95, James A. Sweet and Larry L. Bumpass, P.I.s, funded by the Center for Population Research of the National Institute of Child Health and Human Development grant HD-21009).

Figure 5.

Tolerance for increased depression by age at baseline, assuming good subjective health and no physical impairment at baseline. Tolerance is the increase in depression above which a person drops out of the survey. The predicted increase adjusts for tolerance, the observable increase does not. (Mirowsky and Reynolds 2000, U.S. NSFH data).

Figure 6.

Aging vector graphs showing two patterns of change in sense of control that are equally consistent with the baseline observations: a hypothetical trajectory with no trend between cohorts (top), and the actual trajectory with a trend toward higher values at younger ages (bottom).

Figure 7.

Synthetic and virtual cohort curves for persons age 21 at midpoint, superimposed on the aging vectors and their levels at midpoint. To illustrate the scale of the vectors and their projections, the Y-axis shows the percentile ranks of the Z-scores for the values ranging from 0 to 1.6 at 0.2 unit intervals, with a mean of .794 and standard deviation of .438.

Figure 8.

Exploratory virtual cohort curves for three cohorts, assuming linear age-specific trends. The difference projected between two cohorts at a given age is the trend at that age multiplied by the number of birth years that separate the cohorts (24 years in this example).

Figure 9.
Virtual cohort curves for depression (days per symptom per week).

Figure 10.

The trend-function method for graphing a virtual cohort curve: multiply the age-specific trend by the number of years until the reference cohort reaches each age and add it to the cross-sectional level at that age. The vertical gap between dashes represents the rate of the trend over six years (to make the gaps visible). The number of dashes between the curves represents the number of 6-year intervals until the reference cohort reaches that age.

Table 1

Computation of the virtual cohort curve $V(A_{i0})$ for the reference cohort age k at time zero.

Column:	1	2	3	4	5	6	7	8
	$\hat{a}_i$	$\hat{b}_i$	$\frac{\hat{a}_i}{(A_{i0} - k)}$	T_i	$T_i(A_{i0} - k)$	$V(k)$	$V(k+24)$	$V(k+48)$
$f(A_{i0})$								
$(A_{i0} - k)^0$	.914	.033	.543E-2	2.757E-2		.914	.252	-.409
$(A_{i0} - k)^1$	.543E-2	-8.3003E-4	-4.376E-4	-3.924E-4	2.757E-2	.033	.042	.052
$(A_{i0} - k)^2$	-2.188E-4				-3.924E-4	-6.122E-4	-6.122E-4	-6.122E-4

Notes:

$\hat{a}_i$ = the predicted level of perceived control at time zero (midpoint of the followup interval); the cross-sectional curve at mid followup.

$\hat{b}_i$ = the predicted annual change in perceived control over the followup interval.

$\frac{\partial \hat{a}_i}{\partial (A_{i0} - k)}$ = the cross-sectional slope with respect to age.

T_i = the trend function = the followup slope minus the cross-sectional slope; the predicted rate of change across cohorts as a function of age at mid followup.
 $= [.033 - .543E-2] + [-8.300E-4 - (-4.376E-4)](A_{i0} - k)$.

$T_i(A_{i0} - k)$ = the age-specific trend times the number of years until the reference cohort reaches each age.

$V(k)$ = the virtual cohort equation for the reference cohort

$= \hat{a}_i + T_i(A_{i0} - k)$

$= .914 + [.543E-2 + 2.757E-2](A_{i0} - k) + [-2.188E-4 + (-3.924E-4)](A_{i0} - k)^2$

$V(k+24) = V(k) - 24T_i$

$= [.914 + (-24 \times 2.757E-2)] + [.033 + (-24 \times -3.924E-4)](A_{i0} - k) - 6.122E-4(A_{i0} - k)^2$

$V(k+48) = V(k) - 48T_i$

$= [.914 + (-48 \times 2.757E-2)] + [.033 + (-48 \times -3.924E-4)](A_{i0} - k) - 6.122E-4(A_{i0} - k)^2$