Later-Life Economic Inequality in Longitudinal Perspective

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Data from the National Longitudinal Survey of Older Men were used to estimate economic inequality within three 5-year cohorts as they moved from midlife to later life. The Gini index of inequality increased steadily after age 59, supporting the hypothesis that within-cohort inequality increases in late life. However, a transition analysis found considerable mobility in relative status for individuals over a 15-year period. These results suggest the need to develop a longitudinal perspective on later-life economic status which distinguishes between individual-level and population-level outcomes and identifies the life events and characteristics of individuals that predict changes in economic status. Further research is needed on the processes which lead to later-life inequality, and on the distributional impact of public and private pension policies.

ECONOMIC well-being in later life is a central concern for gerontological social policy and is the object of extensive income transfer and benefit systems. However, the determinants of economic well-being in later life, and the distribution of outcomes which ensue, are insufficiently understood. It is generally accepted that mean income peaks in midlife and declines in late life, but analyses vary as to the age at which income peaks and the typical size of the subsequent decline. An important question is whether economic inequality increases or decreases with advancing age. No consensus exists with respect to this apparently straightforward question (Crystal and Shea, 1990a), which we address in this article with longitudinal data.

Understanding income distribution among older Americans has a variety of important implications for policy. Later-life income distribution varies considerably among developed countries (Smeeding, Torrey, and Rainwater, 1993), and is shaped not only by the numerous vicissitudes of individual life events and choices, but also by policy choices implicit in the design and regulation of retirement income systems (Crystal, 1984). While working-age adults receive most of their income from the labor market, most of the income of older persons in the United States derives from transfer payments aimed at assuring adequate retirement income, funded either directly from governmental sources or from government-regulated, tax-advantaged private pension systems. Individually purchased retirement accounts, also government-regulated and tax-advantaged, play an increasingly important role in the retirement income stream as well. Policy decisions concerning the rules of public and private retirement income systems have important distributional consequences; in making such decisions, information about the net distributional impact of the present system as well as the probable consequences of specific elements or changes therein is an important starting point.

Reflecting public and legislative concerns about adequacy and equity of outcomes, the Social Security system incorporates explicit “leveling” provisions which return a higher percentage of preretirement income, and a higher rate of return on contributions to the system, for lower-income workers than for higher-income workers. However, cross-sectional analyses suggest that the effects of these mildly redistributive Social Security rules on total income are outweighed by the unequalizing effects of other retirement income sources (Crystal and Shea, 1990a). Considering the scale of governmentally sponsored or regulated income transfers to older Americans and their cost to working-age individuals, it is important to understand as much as possible about issues of equity in the retirement income system and to understand the net pattern of financial outcomes it produces for the older age group. Analyzing change in the level of income inequality within a cohort as its members move from their working years to their retirement years provides a picture of the pattern of net outcomes produced by the retirement income system in later life, as compared to the pattern of outcomes produced in midlife largely through the direct consequences of the labor market. This article provides distributional analyses at the aggregate level and analyses of transitions at the individual level; such analyses are complementary, providing different perspectives on later-life outcomes. While needing to be supplemented by other information, income distribution outcomes are a significant and under-researched piece of the puzzle that needs to be assembled to adequately understand the impact of policy choices on financial outcomes for older individuals.

Empirical estimates of income distribution in relation to age have varied, and are affected by a variety of conceptual, methodological, and data choices and problems (Crystal, 1986). Most published analyses of later-life economic well-being have relied on cross-sectional age comparisons, which confound within-cohort trajectories and between-cohort differences (Jianakoplos, Menchik, and Irvine, 1989). While a few longitudinal studies have followed cohorts into at least the earlier years of old age, there has been little use of such data to estimate what happens to the level of inequality within a cohort as it ages. There has been somewhat more
attention to the predictors of individuals’ economic status at different ages and of transitions in economic status, often across relatively brief spans. In one significant study, for example, Leon (1985) analyzed the determinants of income before and after retirement using Panel Study of Income Dynamics (PSID) data, suggesting that preretirement economic status is largely perpetuated in postretirement status. Leon’s analysis focused only on the year before and the year after retirement, with a sample of 285 household heads who did not experience a change in household composition.

Later-life economic outcomes for individuals involve a complex set of relationships over time among employment history, program structure and eligibility, and life events such as disability and widowhood. There is a shift of principal income sources from the labor market to public and private retirement income systems. The pattern of outcomes which ensues as these shifts take place reflects the structure of retirement income systems in interaction with the consequences of individual events and choices over the life course. In analyzing these outcomes, a number of studies have taken an “event-based” approach to later-life economic status, focusing on the relationship between experiencing a substantial decline in economic well-being in later life (e.g., falling into poverty) and events such as retirement and the death of a spouse (Burkhauser, Butler, and Holden, 1991; Burkhauser, Butler, and Wilkinson, 1985; Burkhauser and Duncan, 1988, 1989; Burkhauser, Holden, and Feaster, 1988; Hurd and Shoven, 1988). The death of a spouse appears to substantially increase the probability that an elderly woman will fall into poverty, but has less impact on the risk of poverty for men. While public and private pension programs often moderate the impact of retirement, dramatic income changes sometimes take place at this time: Burkhauser and Duncan (1989) found that in 7 percent of cases, retirement is associated with at least a 50 percent decrease in economic well-being. Changes in health status are also associated with downward changes in economic well-being (Burkhauser, Butler, and Wilkinson, 1985).

“Event-based” studies have been important in beginning to understand the impact of major life events on economic outcomes, and more such is needed. Less attention has been paid to change in overall income distribution within cohorts as they age. As a cohort progresses from midlife to late life, shifting from the labor market to the retirement income system as the principal source of income, does inequality increase or decrease? Information on inequality is only one of the relevant criteria by which a nation’s retirement income institutions can be evaluated; we also need to know more about the types of income changes experienced by differently situated individuals and the way in which these changes drive observed changes in income distribution. Before interpreting within-cohort changes in income distribution, however, we need first to estimate these distributional changes.

Results of such analyses can shed light on the applicability of alternative theories of later-life income dynamics. Because of the important role of Social Security pensions in the retirement income stream, it has often simply been assumed that post-retirement economic resources are more equally distributed than those before retirement age. A theoretical perspective with different implications, the “aged heterogeneity” perspective, notes that in the latter part of the life cycle, aging is associated with a tendency to increased heterogeneity with respect to a wide variety of psychological, social, biological, and other characteristics (Dannefer and Sell, 1988). This would suggest that economic differences as well might tend to increase in later life, at least in the absence of strongly redistributive policies. Thus, it is not clear what the net effect of aging on income distribution in later life would be expected to be. Empirical studies have variously characterized the process as one of leveling (Fuchs, 1984; Hurd and Shoven, 1985; Pamperl, 1981), status maintenance (Henretta and Campbell, 1976; Leon, 1985), and cumulative advantage/cumulative disadvantage (Crystal and Shea, 1990a, 1990b).

The leveling hypothesis posits that the increased later-life role of public benefit programs is particularly beneficial to lower-income individuals and leads to a narrowing of the income distribution. Fuchs (1984), for example, stated that “... income is more equally distributed after age 65 than before that age. ... The principal reason for the narrowing of inequality after age 65 is that Social Security benefits become more important and labor income less important, and the former is distributed much more equally than the latter.” Hurd and Shoven (1985), using data from the Social Security Administration’s Retirement History Survey, reported that during the 10 years of the survey, “... real income of the lower tail of the distribution has increased. This is due to the sharp increase in SSI, Medicare, and Social Security for this population. ...” This finding appears to result in significant part from the study’s attribution of the per capita cost of Medicare to each individual as though it were cash income, an approach which is controversial (Radner, 1992).

The “status maintenance” position was articulated by Henretta and Campbell (1976). Based on findings from a repeated cross-section (“pseudo-cohort”) analysis, they argue that “... the factors which determine income in retirement are the same ones that determine income before retirement.” A “status maintenance” interpretation would suggest that retirement income institutions perpetuate individuals’ preretirement relative economic status, and would predict a relatively limited degree of turnover in relative position. The prediction of a “status maintenance” position as to the overall extent of inequality in the later-life income distribution is not entirely clear; the assertion that the relative status of individuals is maintained, with the same factors predicting preretirement and postretirement status, would appear to be consistent with either narrowing or widening of the income distribution.

The cumulative advantage/cumulative disadvantage hypothesis suggests that some effects of early head starts and handicaps may cumulate over the life span through a variety of mechanisms; for example, “better” jobs may be even more sharply distinguished from “worse” jobs by their benefits than by their salaries (Crystal and Shea, 1990a). To the extent that these effects outweigh any redistributional effect of Social Security and means-tested benefits, this would predict an increase in the overall level of economic
inequality within a cohort as it ages. A "cumulative advantage" position would imply that individuals with economic disadvantages that begin early in the life course, such as limited education or minority-group membership, would not on average improve their relative or absolute economic position in later life. However, such a view is not necessarily inconsistent with turnover in the income distribution. For example, a scenario in which modestly paid teachers and ministers with good pension plans were to improve their relative position after retirement, where commercial fishermen and welders without pension plans were to experience declines, would be entirely consistent with a "cumulative advantage" model.

In characterizing the dynamics of economic well-being in later life, an important and often-neglected conceptual distinction is between individual and population dimensions of the process. Collectively, the dispersion of income may decrease, stay the same, or increase as a cohort ages. An entirely distinct question is the extent to which individuals do or do not maintain their relative positions within the distribution. Addressing this question requires data which follow individuals over time. The distinction between individual and population dimensions of income dynamics can easily be missed in interpreting studies based on cross-sectional data. For example, findings by Henretta and Campbell (1976) and by Crystal, Shea, and Krishnaswami (1992) that such social background characteristics as education are predictive of income after age 65 as before do not directly address the question whether individuals remain at the same relative economic status position, although Henretta and Campbell interpreted such findings as implying "status maintenance."

While longitudinal data are essential to a satisfactory understanding of later-life income dynamics, such data are scarce, expensive to collect, and suffer from problems of their own such as sample attrition. Thus, most work on income distribution in relation to aging has utilized cross-sectional data. Some cross-sectional studies have shown that income inequality, as measured by the Gini coefficient, is higher for older individuals than for younger age groups (Crystal and Shea, 1990a; Deaton and Paxson, 1994; Radner, 1987; Taussig, 1973). Such results tend to contradict the leveling hypothesis. Crystal and Shea (1990a), for example, constructed a measure of economic well-being that took account of household composition, assets, and underreporting of some income types, using data from the 1984 panel of the Survey of Income and Program Participation (SIPP). In this cross-section, inequality decreased with age up to ages 35-44 and increased with age at older ages, with a Gini coefficient of .415 at ages 75+. These high levels of inequality are a concern since they suggest that despite mean incomes for older Americans which compare favorably with those of nonelderly persons (Crystal and Shea, 1990b), those elderly persons in the lower part of the income distribution share in this bounty only to a very limited extent; at ages 75+, the less well-off 40 percent shared less than 15 percent of their age group's total income.

Since elderly and nonelderly individuals in this study were members of different birth cohorts, however, one cannot unambiguously attribute cross-sectionally observed differences to age rather than to cohort effects. The older individuals among whom observed inequality was higher may represent a "high-inequality cohort," characterized by a high Gini coefficient at earlier ages as well. Further, the comparison of population distributions by age tells us nothing about the stability of relative position for individuals. An additional problem is the effect of differential survival on income distributions by age. If, for example, individuals in the upper and lower extremes of the distribution were more likely to survive than those in the middle, differential mortality might account for an apparent increase in inequality with age. In cross-sectional studies, one cannot observe and correct for the effects of differential survival, since it is unknown which of the individuals observed at younger ages will survive to older ages.

Despite these methodological problems with analyses from cross-sectional data, however, such work, along with studies suggesting that income inequality among older persons in the U.S. is substantially higher than is the case in most developed countries (Smeeding, Torrey, and Rainwater, 1993), leads us to hypothesize that inequality within a cohort will increase with age as the cohort moves from midlife to later life. This hypothesis is also consistent with the "aged heterogeneity" perspective suggested by Dannefer and Sell (1988) and discussed above. In a similar vein, it has been suggested by some economic theorists that the permanent income hypothesis, predicting that consumption and income from year to year follow a "random walk" pattern, implies that economic inequality should grow with age (Deaton and Paxson, 1994). This theoretical perspective, like the more sociological and epidemiological "aged heterogeneity" perspective suggested by Dannefer and Sell (1988), focuses on the effects of individual life-course events over time, suggesting that the effects of luck will tend to lead to increasing differences. Linking such perspectives with analyses of retirement income policies, the "cumulative advantage" model suggested by Crystal and Shea (1990a) would suggest that in the absence of strongly redistributive retirement income institutions (such as high minimum Social Security benefits), the vicissitudes of life events would lead to higher inequality in later life. Research on the distribution of income from non-public retirement income systems such as private pensions suggests that these income sources tend to be received disproportionately by more advantaged members of the labor force (Crystal, 1984), also supporting the hypothesis that inequality may increase within a cohort as it enters its later years.

In order to adequately test this hypothesis, long-term longitudinal data are required. In the present analysis we use data from the National Longitudinal Survey of Older Men (NLSOM) to characterize income and inequality trajectories for three 5-year cohorts of men followed from midlife to late life. We also use these data to investigate the extent of movement of individuals within the income distribution over an extended (15-year) period of time.

METHODS

Data and Measures

Baseline interviews for the NLS Older Men cohort were
conducted in 1966, providing data on 5020 men aged 45 to 59 in that year. The survey used a multi-stage probability sample designed to represent the civilian noninstitutionalized population of the United States for men of the specified ages and their households (Parnes, 1981). Respondents were drawn from 235 primary sampling units representing every state. We used data collected in 1966, 1971, 1976, and 1981 personal interviews on income during the previous year. Representing a 15-year span of ages at baseline, the respondents were divided for analytic purposes into three 5-year cohorts, each followed for a 15-year period. The overlapping trajectories of these three cohorts provide a perspective which extends from ages 45–49 (Cohort 1 at baseline) to ages 70–74 (Cohort 3 in 1980).

The basic measure of income in the NLSOM data is family income of sample individuals. Use of family income to measure economic status requires an adjustment for the number of individuals who must share that income. An adjustment that is sometimes used is to divide family income by the size of the family to obtain per capita family income. However, this approach does not consider economies of scale in household expenses. A two-person home does not need twice as many kitchens, refrigerators, or square feet as a one-person household. We use a fairly standard poverty line (Orshansky scale) based adjustment which is intermediate between no adjustment and per capita family income (Crystal and Shea, 1989; Danziger et al., 1984a, 1984b; Moon, 1977; Ruggles, 1990; Smeeding, 1977). The adjustment factor is calculated by taking the ratio of the poverty level for a given household’s size to that of a one-person household.

A potential problem in the analysis is top-coding. Family income reported for 1965 and 1970 was top-coded at $50,000 (current dollars). Two percent or fewer of the reported incomes in these years were top-coded. Family income reported for 1975 and 1980 was top-coded at $120,000 and $121,000, respectively. Only one observation in each of these years was reported at these cutoff levels. In 1987 dollars, the cutoff level for the last time point, 1980, is quite similar to the cutoff level for the first time point, 1965 ($146,289 and $158,100, respectively). Our primary measure of income inequality, the Gini coefficient, is potentially sensitive to top-coding. In order to exclude the possibility that our results are artifacts of top-coding, we also performed similar analyses using a number of other measures of inequality that are unaffected by top-coding at these levels, with similar results.

Survey attrition and item nonresponse are a substantial problem in longitudinal surveys of such long duration, and the NLSOM is no exception. Our measure of income could be missing for two reasons: item nonresponse or unit nonresponse (respondent not interviewed at a particular wave). Item nonresponse occurs when a respondent fails to answer the questions regarding family income or family size (both of which are necessary in order to calculate our measure of adjusted family income). In each of the years 1966, 1971, 1976, and 1981, approximately 20 percent of respondents failed to report family income or family size. The number of missing values due to noninterview increased as time went on: 845 in 1971, 1533 in 1976, and 2188 in 1981. By 1981, 60 percent of all missing observations were due to the death of the respondent.

In order to assess and mitigate potential biases caused by unit or item nonresponse, we have computed the results separately for two samples, ‘survivors’ and ‘everyone.’ In the ‘survivors’ analysis, we drop any observation that has a missing value at the first or last observation (that is, missing in the 1966 or the 1981 interviews). Since missing values could arise due to either attrition or item nonresponse, some observations dropped from the survivors sample are due to item nonresponse in 1966. In the ‘everyone’ analysis, the results for a given period represent all of the data available for that period.

To the extent that changes in the composition of the ‘everyone’ sample match the changes in the population, the ‘everyone’ sample will provide a good estimate of inequality changes at the population level. Therefore, the results from the ‘everyone’ sample are the most relevant for understanding income adequacy and needs within the population actually surviving to the 65+ age. However, if attrition and item nonresponse in the ‘everyone’ sample differ substantially from changes in the true population, then our estimates of income inequality could be subject to the criticism that they are caused by these changes in the sample over time. Therefore, we also present results from the ‘survivor’ sample since the ‘survivor’ sample, for the most part, follows the same individuals over time and, thus, measures changes in the distribution of income of this ‘fixed’ sample. The ‘survivor’ analyses filter out the effects of differential mortality or loss-to-followup on income distribution within a cohort over time. The major aim of analyzing inequality trends in both ways is to determine whether these observed trends are robust with respect to alternative definitions of the population in question. If results are similar in both kinds of analyses, as they turn out to be, the inference is strengthened that there is a true within-cohort increase in inequality over time, which is not accounted for simply by compositional change in the cohort and which describes the level of inequality among those surviving to various ages.

Measurement of Income Inequality

Measures of income inequality are essentially dispersion measures of the distribution of income. Most analyses of income inequality rely on single-value measures such as the commonly used Gini coefficient, since measures that cannot be summarized by a single value provide only an incomplete ranking of income distributions. The measurement of income inequality involves a number of problems. The concept of inequality has been operationalized in several different ways, with the Gini coefficient one of the most widely used. Unlike quintile-based measures, which are also commonly used, the Gini coefficient is independent of the units used to measure income. Any mean-preserving spread applied to a distribution will cause the Gini coefficient for that distribution to increase.

Analyses utilizing Gini coefficients have often lacked confidence intervals or hypothesis tests for differences in coefficients, since these calculations are somewhat difficult (particularly for weighted data, which do not necessarily
represent a well-defined distributional form). Even though variance estimators for the Gini coefficient from unweighted data have long been available (Glasser, 1962; Hoeffding, 1948), tests relating to the sampling distribution of the Gini coefficient are, according to Yitzhaki (1991), “seldom” performed due to the complexity of the variance estimators. In the present study, we used a bootstrap resampling method to perform rank tests on the estimated Gini coefficients. This procedure also addresses the possibility that estimates are sensitive to measurement error at the extremes of the distribution. If a small number of observations have a large impact on the Gini coefficient calculation, the resampling method will detect this by estimating a wider sampling distribution for the coefficient. The present study uses samples of quite substantial size and, as will be noted, most observed differences are statistically significant.

Estimation of Gini coefficients and their confidence intervals with this data set must take account of the weighted sampling in the NLS. Let \( i = 1, \ldots, k \) index individual observations in the data such that the data are in ascending order by income (\( k \) denotes the number of observations). The income and sampling weight for the \( i \)th observation are \( n_i \) and \( w_i \), respectively. The formula for the Gini coefficient for weighted data can be written as

\[
G^* = 1 + \frac{1}{\sum_{i=1}^{k} w_i} \frac{2 \sum_{i=1}^{k} \sum_{j=1}^{i-1} (j + \sum_{k=1}^{i-1} w_k)n_i}{\sum_{i=1}^{k} \sum_{j=1}^{i-1} w_j n_i}.
\]

When the sampling weights \( w_i \) are constant across observations, the above expression reduces to the formula for the Gini coefficient given by Sen (1973).

Cowell (1989) provides an unbiased estimator for the Gini coefficient calculated from a weighted sample. However, Nygård and Sandström (1989), in a Monte Carlo comparison of explicit variance expressions and resampling estimates of the sampling distribution of the Gini coefficient, find no statistical basis to prefer either technique. In this application, we opted to use a resampling technique for hypothesis testing on the estimated Gini coefficient. A bootstrap sample was constructed by randomly sampling with replacement from the original sample until the sum of the weights in the bootstrap sample was (approximately) equal to the sum of the weights in the original sample. A Gini coefficient was then calculated from the bootstrap sample. We repeated this procedure 1000 times. The resulting set of 1000 Gini coefficients is an empirical estimate of the sampling distribution of the Gini coefficient from the original sample and is used to test the significance of differences in coefficients from one wave to the subsequent wave. A rank test is used to evaluate the hypothesis that the two empirical distributions were drawn from the same underlying distribution. Let \( F_i \) and \( F_j \) represent the cumulative distribution functions of the two sampling distributions. The test assumes that \( F_i(x) = F_j(x + \alpha) \). The null hypothesis is that \( \alpha = 0 \), and the alternative hypothesis is that \( \alpha \neq 0 \).

A potential weakness of the Gini coefficient is its sensitivity to changes in the tails of the distribution. Such sensitivity may be a problem if the data are top-coded or if there is measurement error in the tails. To demonstrate that our conclusions are robust, we confirmed our results with similar analyses using three other measures of income inequality: the coefficient of variation, the lower quartile of income as a percentage of the upper quartile, and the interquartile range as a measure of the lower quartile. While the coefficient of variation is sensitive to small changes in the tails of the distribution, our other two measures will be unaffected.

To help inform our analysis of income inequality, we present a number of results relating to the degree of individual mobility within the distribution of income. While related to inequality, high degrees of mobility can persist in the presence of increasing, decreasing, or constant inequality. For example, if two individuals switch incomes, then inequality remains unchanged but mobility exists within the income distribution.

**RESULTS**

Figures 1 and 2 report average real adjusted income by cohort. Figure 1 depicts the results for the “everyone” sample, and Figure 2 depicts the results for the “survivors” sample. The “survivors” group includes all individuals with nonmissing observations of income at the first and last wave. For the “survivors” group the sample size is the same for the first and last wave for each cohort, but at the second and third waves the sample sizes are slightly smaller. This occurs because some of the individuals with nonmissing observations at the first and last waves have missing values on the intervening observations. In the “everyone” sample all of the nonmissing observations in a given wave were used to calculate the average. The sample sizes in the “everyone” analysis are substantially larger than in the “survivors” analysis.

For cohorts 1 and 2, adjusted real income peaks at 55–59 years of age for both “survivors” and “everyone.” For cohort 3 adjusted real income peaks at 60–64 years of age. This difference in the peak earning years may be due to a period effect. Note that cohorts 1 and 2 had large increases in average income from the first to the second observations (from 1965 to 1970). The period between 1965 and 1970 was one of strong real income growth in the United States, which may have resulted in a later age peak for the oldest cohort.

**Income Distribution**

Within each cohort, Gini coefficients were calculated at each wave. Because of the identification problem among age, cohort, and year of observation (any two of these define the third), it is not possible to identify age, cohort, and year effects on the level of inequality unambiguously and simultaneously. However, one can make comparisons with such data two dimensions at a time: in particular, one can compare the level of inequality within each cohort as it reaches different ages, and one can compare the level of inequality by age group at each time of observation. For survivors, these results are depicted in Figure 3. Because we wished to test the hypothesis that inequality within each cohort increased as the cohort aged, we focused particularly on comparing within-cohort inequality as the cohort reached different ages (reading down the columns of Figure 3). However, since each 5-year cohort was observed at 5-year intervals, the results form a matrix which can also be read
across (comparing cohorts with respect to inequality at a given age), or diagonally (showing cross-sectional comparisons by age at each year of observation). Read diagonally, as indicated by the shading, Figure 3 shows a higher level of inequality among older respondents; this pattern was observed at each time of observation. For example, in 1980 the Gini coefficient was .369 among persons 60–64 and considerably higher, .452, among persons 70–74. These cross-sectional comparisons both for “survivors” and for “everyone” indicate that the Gini coefficient was higher at the older ages, at each time of observation, consistent with the cross-sectional findings reported by Crystal and Shea (1990a) using SIPP data.

Reading across the rows of Figure 3, we can compare cohorts with respect to the level of inequality experienced at the point that the cohort reaches a given age (which was attained at different calendar years by each cohort). At ages 55–59 and 60–64, where we can compare all three 5-year cohorts, the level of inequality was higher in the oldest than in the youngest 5-year cohort, with the middle cohort experiencing an intermediate level of inequality. At ages 65–69, where we can compare the older two cohorts, there was essentially no difference between them (Gini coefficients of .422 and .425, respectively).

When within-cohort change in income distribution was examined, a pattern of increasing inequality over time was evident, both in “survivors” and in “everyone” analyses. Figures 4 and 5 provide a graphic depiction of the “trajectory of inequality,” as indicated by the Gini coefficients within each cohort as the cohort aged. For each cohort in
both types of analyses, there was a significant and substantial increase in the Gini coefficient from the first observation to the last. In the “survivors” analysis of the oldest cohort, for example, the coefficient increased from .391 at ages 55 through 59 to .452 at ages 70 through 74. These results show that inequality did increase within each cohort as it aged.

In order to test for significant differences between the Gini coefficients, an empirical sampling distribution of 1000 resamplings was constructed for each Gini coefficient presented in Figures 4 and 5 using the bootstrap technique discussed above. We then used a rank test to evaluate changes in income inequality over time for each cohort. We also tested for differences in income inequality across cohorts at each time period and at each age. The null hypothesis that there is no change was rejected in every case (at a 95% level) except in the comparison of the “everyone” Gini coefficients for cohort 1 at ages 45–49 and 50–54.

We also measured inequality using the coefficient of variation, the lower quartile of income as a percentage of the upper quartile, and the interquartile range as a percentage of the lower quartile. The last two of these measures are insensitive to errors in the tails of the distribution of income. These alternate measures indicate an increase in inequality from the 1966 interview to the 1981 interview for all three cohorts and both samples. For instance, in the survivors sample the interquartile range as a percentage of the bottom quintile increased from 1.4 to 1.8 for Cohort 1, from 2.0 to 2.4 for Cohort 2, and from 2.0 to 2.3 for Cohort 3.

Individual Mobility

To understand the implications of these patterns of inequality over time, it is also important to determine the extent of individual mobility within the income distribution. Studies of such shifts have often focused on the proportion of cases which experience transition from one status to another, such as from nonpoor to poor. It is useful, however, to utilize approaches which distinguish large changes from small ones and which provide information on the size of shifts. The median size of transitions upward and downward, and the probability of transition from one income quintile to another, provide complementary perspectives on the extent of income mobility. Table 1 shows the number of cases experiencing increases and decreases in income among survivors in each cohort as the cohort aged by 5-year increments, and the median size of the changes. The sum of the n’s in Table 1 for each cohort represents the total number of survivors with data in each pair of years. Changes in income as cohorts aged from 45–49 to 50–54 and from 50–54 to 55–59 were more likely to be upward than downward in each cohort, and the median size of upward changes was larger. Change in income from 55–59 to 60–64 varied somewhat by cohort and year of observation, involving frequent change in both directions. Changes in income from ages 60–64 to ages 65–69, and from ages 65–69 to ages 70–74, were about twice as likely to be downward as upward, and downward changes tended to be somewhat larger than upward changes. In Table 1, even a small increase or decrease counted as a positive or negative change. However, the typical magnitude of changes was substantial: the median absolute percentage change in real income ranged from 27 percent to 41 percent, with the largest changes occurring as individuals in Cohort 2 went from ages 60–64 to ages 65–69 and as they went from ages 65–69 to ages 70–74.

While Table 1 illustrates changes in real income, which reflect both the changing fortunes of the cohort and movement within it, Tables 2 and 3 focus on individual shifts within each cohort’s income distribution, that is, change in status relative to one’s peers. Shifts were computed for 5-year, 10-year, and 15-year periods. Table 2 shows the matrix of transition probabilities, for the full 15-year period, from one quintile in the income distribution to another. Quintiles are numbered from 1 (best-off) to 5 (worst-off); baseline quintiles are defined on the basis of an individual’s adjusted family income in 1965, and ending quintiles are defined on the basis of an individual’s adjusted family income in 1980. Rates of transition were substantial. In Cohort 1, for example, members of the poorest quintile at baseline had a 46.6 percent chance of being in the poorest quintile in 1980, so that more than half had shifted from this disadvantaged position. Probabilities along the diagonal of the matrix correspond to no change in quintile. Except for the upper left-hand corner and the lower right-hand corner of each matrix, the probabilities along the diagonal are generally less than .30. That is, if an individual was in either the second, third, or fourth quintile at the baseline observation, then he had less than a 30 percent probability of being in the same quintile at the last observation. The higher stability rates in the upper left-hand and lower right-hand are influenced by ceiling and floor effects, i.e., movements from the best-off quintile can only be downward and vice versa.

In order to show 5-year as well as 15-year patterns of transition and to distinguish transitions to adjacent quintiles (which could be caused by small shifts) from larger changes, Table 3 collapses the transition matrix to show the probabilities of a change upward or downward of more than one quintile. Such changes represent sizable movements in relative position within the distribution of income. To simplify the interpretation, increase cell sizes, and include shifts up to the 65–74 age range, Cohorts 2 and 3 were merged and
Figure 4. Gini coefficients by age and cohort (all subjects).
*This Gini coefficient is not significantly different from the coefficient for Cohort 1 at ages 50–54.

Figure 5. Gini coefficients by age and cohort (survivors).

Table 1. Median Percentage Change in Real Income for Survivors

<table>
<thead>
<tr>
<th>Change in Age</th>
<th>Cohort 1</th>
<th>Cohort 2</th>
<th>Cohort 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Negative Change</td>
<td>Positive Change</td>
<td>Negative Change</td>
</tr>
<tr>
<td>45–49 to 50–54</td>
<td>18% (n = 107)</td>
<td>46% (n = 371)</td>
<td>18% (n = 122)</td>
</tr>
<tr>
<td>50–54 to 55–59</td>
<td>24% (n = 150)</td>
<td>31% (n = 237)</td>
<td>30% (n = 176)</td>
</tr>
<tr>
<td>55–59 to 60–64</td>
<td>30% (n = 262)</td>
<td>32% (n = 209)</td>
<td>29% (n = 246)</td>
</tr>
</tbody>
</table>
Cohort 1 was not included. The first three columns of Table 3 label the quintile at the beginning of the transition and provide the sample sizes. The last four columns of the table present the results; the dates across the top label the period of transition. The first two lines represent (downward) movement of more than one quintile from positions in the best-off two quintiles. The third line contains two probabilities, one pertaining to movements down of more than one quintile and one pertaining to movements up of more than one quintile. The fourth and fifth lines represent (upward) movement of more than one quintile from positions in the worst-off two quintiles.

Table 3 shows that even when attention is restricted to substantial changes in position (more than one quintile), a considerable proportion of respondents changed their position over a 15-year period. For example, among those in the top quintile in 1965, 28 percent were in the third quintile or below in 1980. Of those in the lowest quintile in 1965, 19 percent were in the third quintile or higher in 1980. When movements from the highest and lowest quintile are compared, it is evident that in the first two transition periods, movement from the top quintile substantially downward (by more than one quintile) is more prevalent than substantial movement from the bottom upward. However, in the last transition period, from an average age of 65 to an average age of 70, more individuals in the lowest quintile substantially improved their position than individuals in the highest quintile moved downward.

**DISCUSSION**

Variations in age of retirement, pension coverage, health and marital status, and many other intervening variables shape the distribution of later-life economic outcomes and the distribution of income in later years. Through this research we aim to characterize the overall extent of inequality and mobility within the income distribution that is the net result of these processes in later life. The results support the hypothesis that income distribution within each cohort increases as the cohort passes into later life. This pattern was found both in ‘survivors’ and ‘everyone’ analyses, suggesting that the pattern is robust and that the increase is not simply the result of changes in cohort composition such as disproportionate mortality at the extremes of the distribution. The high level of economic inequality in later life and the pattern of increase with age suggest that there may be a need to reexamine the degree of protection which retirement income policies provide to less-advantaged elderly individuals and to those who experience adverse life events that can threaten their economic well-being.

Over this relatively restricted range of cohorts, representing a 15-year span of birth years, the oldest of the three 5-year cohorts appears to have experienced higher inequality than the younger cohorts at a given age for ages under 65. However, by age 65–69, convergence was seen both in ‘everyone’ and ‘survivors’ analyses between the level of inequality of the oldest and the middle cohorts, the two cohorts which reached that age during the period of observation. Indeed, the two younger cohorts appear to have experienced a sharper within-cohort increase in inequality after age 59 than was the case for the older one. Because of the within-cohort increases, inequality reached a very high level (Gini higher than 0.4) after age 65 for both 5-year cohorts that were followed to that age range.

By themselves, of course, the distributional findings provide only part of the picture needed to understand the consequences of policy choices. The characterization of these distributional outcomes needs to be followed up with more work on the processes which produce these levels of inequality among the older population. Through this research we aim to characterize the overall extent of inequality and to those who experience adverse life events that can threaten their economic well-being.
inequality. Two important lines of work involve longitudinal analyses of outcomes experienced by differently situated individuals, and of the distributional impact of specific income sources. Employment income received by individuals over age 60 and especially by those over age 65 appears to be one unequalizing factor (although it should be noted that inequality in our study was even higher after age 70, when few individuals were still working). Private pension income is another major unequalizing factor: such income is received mostly by individuals with the highest incomes from Social Security and other sources (Crystal and Shea, 1989, 1990a). Social Security income is more equally distributed than is total income (Crystal and Shea, 1990a), but the redistributive elements in Social Security formulas do not appear to be sufficient to produce a "leveling effect" for total income after retirement age.

Another perspective on the processes which may be leading to the observed high level of inequality observed at the later ages can be gained by comparing inequality indices for elderly persons across countries with differing retirement income systems, using cross-sectional census data. Benefits (both public and private) that are directly related to the level of preretirement contributions play a larger role in the U.S. than in most developed countries for which comparative data are available, while public flat-rate benefits, minimum benefits, and means-tested programs play a smaller role. Smeeding, Torrey, and Rainwater (1993), in a comparison of eight developed countries, found that minimum benefits in the U.S. were the smallest among the countries in proportion to median income for people of all ages. Social insurance such as Social Security retirement pensions and means-tested income combined accounted for 58 percent of the income of elderly people in the U.S., a lower figure than for any of the other countries. The relatively limited role of flat-rate, minimum, and means-tested benefits in the U.S. retirement income system, and the prominent role of private pensions, seems to be related to the high level of income inequality among older persons in the U.S. These structural features may interact with individual life events in such a way as to produce outcomes that are problematic from the point of view of equity and adequacy for less-advantaged elderly individuals. Smeeding, Torrey, and Rainwater found that for both the 65—74 and the 75 + age ranges, inequality as measured by the Gini coefficient was higher for the U.S. than for the seven other countries studied.

By their nature, cohort studies provide direct information only on particular cohorts entering old age during particular historical periods. The extent to which the pattern of increasing within-cohort inequality projects to later cohorts can only be answered empirically. What the results do indicate is that over a 15-year period of considerable real income growth for older people, for the cohorts which make up today’s 75 + population, within-cohort inequality increased with time. Members of these cohorts benefited from considerable increases in the real value of Social Security benefits during the early 1970s, but this “rising tide” did not lead to reduced disparity in economic outcomes as cohort members moved into their sixties and seventies.

Our analysis of individual transitions suggests the importance of distinguishing between population-level and individual-level dimensions of the pattern of economic outcomes. These distinctions are often obscured in studies based on cross-sectional data, in which inferences about individual-level outcomes must be made from population-level data. Comparison between cross-sectional and longitudinal results helps to define the several distinct empirical questions which need to be addressed in order to develop a better understanding of later-life economic outcomes. First, what happens to the overall level of inequality within a cohort as that cohort ages? This is a population-level question which describes the distribution of resources within the cohort at a given time as it reaches various ages. A high and increasing level of inequality implies a “two worlds of aging” pattern of outcomes (Crystal, 1984), but does not tell us whether economically advantaged elderly persons are the same individuals who were economically advantaged earlier in the life course. The present longitudinal analysis of SIPP data is consistent with cross-sectional analyses of SIPP data (Crystal and Shea, 1990a) in suggesting that the level of population inequality increases after age 65. A second and distinct set of questions concerns the extent to which economic status is maintained over time for individuals. Here, the longitudinal results suggest a fairly substantial level of turnover in the distribution, suggesting that individual status is not necessarily maintained.

Measuring the degree of stability through transition matrices adds another dimension to the picture provided by the distributional analysis and suggests several further questions as a focus for future research. The results tend to disconfirm the claim that later-life outcomes are characterized by “status maintenance.” It could be argued (as it has for economic mobility at younger ages) that these results mitigate the problematic nature of the high level of inequality observed among older people in the U.S. Certainly, they suggest the absence of a rigid social stratification system by which retirement income institutions perpetuate the economic position occupied by an individual at midlife. However, the implications of large changes in relative status may differ when these changes occur late in life, and depend on who experiences upward and downward changes. Economic mobility in late life, as compared to such mobility earlier in the life course, is less likely to result from the exercise of entrepreneurial initiative, ambition, and talent (or lack thereof) and more likely to result from other factors. Such factors may include, on the one hand, adverse life events such as widowhood, severe illness, or the onset of functional dependency, and on the other hand such aspects of “luck” as good health, good fortune with investments, remarriage, or inheritance. For individuals whose life style was comfortable at midlife, large downward transitions can represent a wrenching readjustment, and we found that such changes (downward transitions of more than one quintile) were not uncommon. For example, among those at the middle level of economic status at baseline at ages 45—59 (those in the third quintile), who were experiencing fairly comfortable circumstances at midlife, 19 percent were in the worst-off quintile 15 years later, representing a poverty or near-poverty life style. These results suggest the need for further research on the life events associated with such transitions, and the degree to which social insurance and other retirement in-
some institutions protect individuals who experience health crises, loss of a spouse, and other catastrophes to which individuals are vulnerable in late life. It has been said that “old age is not for sissies”; social policy usually cannot protect older people from such events, but it can provide some protection from their financial consequences.

In the context of relatively high income mobility in later life, what is the significance of the high level of inequality at these ages and the widening of the income distribution within cohorts? Widening of an income distribution over time tends to magnify the size of transitions within that distribution. Shifts from the middle to the extremes of the distribution will on average be larger than those from the extremes to the middle, producing “big winners” and “big losers” in life’s sweepstakes. The Gini coefficient’s large size at ages over 65 suggests that there is a wide gap in economic well-being between those older people who fall at different positions in the income distribution. Thus, for example, going from the middle to the bottom quintile is a more wrenching transition than would be the case in a narrow income distribution which becomes further compressed as a cohort ages. Similarly, upward transitions in relative status are magnified in a distribution that is widening over time. Indeed, an interesting and under-researched story in gerontology involves understanding the circumstances of those who make large improvements in their relative and absolute economic position after retirement.

From the point of view of equity, adequately interpreting the implications of this set of findings will depend on further research on the circumstances of individuals who ultimately land in the penury represented by the low end of the income distribution or the prosperity represented by the top end. High inequality would not be as much of a concern if the individuals who wind up at the lower end of the distribution were healthy individuals with strong potential support systems, who may not have needed or qualified for public benefits. However, we know from cross-sectional studies that individuals who end up low in the income distribution after age 65 tend to be in poorer health; to have more functional impairments; to have minimal or no financial assets; and to have other characteristics suggestive of long-term economic disadvantage, such as less education and histories of lower-status occupations (Crystal, 1996; Crystal and Shea, 1989, 1990a; Henretta and Campbell, 1976). Crystal, Shea, and Krishnaswami (1992) found that years of education, typically completed before age 30, were more predictive of income after age 65 than earlier in the life course. Mobility in position in the income distribution, as observed in our current study, does not necessarily mitigate the implications of high levels of later-life inequality. Indeed, there is some evidence to suggest that those individuals who are most economically vulnerable (because of limited education, poor health, or other factors) experience the full consequences of their vulnerability only in late life, while those with more advantaged backgrounds benefit disproportionately from “reserve resources” such as health, pension entitlements, and investments at that time (Crystal, 1984; Crystal and Shea, 1990a; Crystal, Shea, and Krishnaswami, 1992).

To understand the extent to which such a scenario is typical, more longitudinal research is needed on which individuals are experiencing what kinds of income changes. What characteristics and life events predict major upward or downward changes in economic status? To what extent, for example, are such changes the result of changes in health and functional status or changes in marital status? Under what circumstances and to what extent does the “social safety net” buffer such changes? To what extent can they be seen as the result of choices made earlier in life, on the one hand, or the result of unpredictable hazards of life, on the other? To what extent do permanent or early-established social characteristics of individuals such as race, gender, parental socioeconomic status, and education predict postretirement-age income? Results of the present study indicate the importance of these research agendas, which require longitudinal data that combine good-quality economic measures with considerable detail on health status, health care costs, functional status, and changes in social circumstances.

This empirical analysis highlights a seeming paradox: increasing inequality at the population level within a cohort as it ages, accompanied by a considerable degree of turnover in relative position. To understand the implications of the individual-level changes, and to inform public policy, more longitudinally based research is needed on the determinants of individual change in economic status, and on the way in which life events and the structure of the retirement income system interact in shaping these outcomes.

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